Aggregation Strategies for SSURGO Data: Effects on SWAT Soil Inputs and Hydrologic Outputs

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The USDA-NRCS Soil Survey Geographic (SSURGO) dataset provides the most comprehensive, detailed soil data coverage across the United States. Correct usage of these data within a hydrologic model depends on assumptions that define how soil property data are aggregated. To reduce data intensity and improve model efficiency, most hydrologic modeling studies using SSURGO assume that soil property data are adequately grouped into some notion of a "soil type" which is represented by the map unit, denoted as map unit key (MUkey), within SSURGO. However, the map unit is not intended for this purpose as continuity in map unit design or composition is not guaranteed between adjacent surveys of different vintages. This causes problems when several survey areas are used together, because similar soils are assigned a different map unit across the boundaries of soil survey maps. We present a methodology for aggregating soil data among multiple soil survey areas according to soil taxonomic information available in SSURGO. Results indicate that the aggregation method provides an acceptable representation of soil parameter values and distributions while eliminating the reliance on an arbitrary map unit for soil type identification. The results of the hydrologic modeling using the Soil and Water Assessment Tool (SWAT) in the San Joaquin River Watershed indicate that the commonly used aggregation method and the newly developed method satisfactorily estimated soil and surface hydrologic processes as compared to using a non-aggregated soil dataset. For the soil hydrologic processes, the SWAT model output from our aggregation method accurately estimated soil water content (mean difference compared to the non-aggregated soil dataset output of −4 mm for western San Joaquin River Watershed subbasins and 15 mm for the eastern San Joaquin River watershed subbasins) and lateral flow (3 mm for the western subbasins and 0.2 mm for the eastern subbasins) as compared to using a non-aggregated soil dataset. For the surface hydrologic processes, the SWAT model under predicted surface runoff (−0.5 mm for the western subbasins and −0.1 mm for the eastern subbasins) and sediment yield (−0.02 t/ha for the western subbasins and -9×10^{-4} t/ha for the eastern subbasins) as compared to using a non-aggregated soil dataset. While some variations were statistically significant, the differences were numerically small. The results show that soil taxonomy provides a robust framework for grouping soils.

Abbreviations: HRU, hydrologic response unit; MD, mean difference; MU, map unit; MUSLE, Modified Universal Soil Loss Equation; RMSD, root mean standard difference; SSURGO, Soil Survey Geographic; SWAT, Soil and Water Assessment Tool.

In the United States, the Natural Resources Conservation Service (NRCS) soil survey maps are one of the most comprehensive spatial environmental datasets and are used as the primary source of soil physical and chemical properties for many surface and subsurface process models. The State Soil Geographic Database (STATSGO) product is a generalized soils map (1:250,000) that is partially based on "more detailed soil survey maps when available", circa 1994. In the absence of more detailed maps, soils of like areas were correlated to remotely sensed and climate data (USDA, 2007b). The most detailed soil survey database from the NRCS, the Soil Survey Geographic Database 2.0 (SSURGO), is available at a range of scales between 1:12,000 to 1:24,000 (USDA, 2007a).

The SSURGO data uses map units (identified with a unique MUkey for each soil survey) to depict patterns of soil component distribution. While the map unit is a useful database construct, the inclusion of multiple soil components in

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the composition of each map unit limits the use of the MUkey as a unique “soil type” identifier. Map unit composition adds considerable complication along with subjectivity to any analysis because the physical location of components within a map unit delineation is *not* explicitly documented. Moreover, map unit composition differs depending on the scale of the survey and land use assumptions made at the time the survey was conducted. For example, in California, consociations dominate the soil survey legend in valley landscape positions where row crops are the main land use. In contrast, complexes are commonly used to describe soil patterns in surrounding terraces and foothill positions, which were traditionally rangeland at the time these soil surveys were made.

A great deal of effort has been invested in the correction of edge-matching errors and normalization of map unit legends in SSURGO 2.0 (Soil Survey Staff, 1999). However, changes in soil taxonomy over time, subtle differences in mapping style between project leaders, and changing views on how soil resources are used have resulted in some irreconcilable irregularities between survey areas. An example of an irregularity is the difference in soil series names along survey boundaries. Additionally, in large states such as California, adjacent soil surveys are mapped by different scientists with the survey date difference of anywhere from a few years to decades, leading to inconsistencies between soil surveys in the soil groups constituting map units. While the SSURGO 2.0 database was specifically developed to minimize discontinuities in map units along soil survey area boundaries, inconsistencies and edge-matching errors remain. This may have serious implications when using SSURGO data for large-scale surface process modeling applications, as landscapes are artificially dissected along political boundaries and soil properties may differ across these lines despite being SSURGO certified (Drohan et al., 2003; USDA, 2009). Regardless of these differences and limitations, SSURGO maps are the highest resolution soil data available and provide valuable, comprehensive soil data input for many modeling applications. On average, SSURGO map units in California occupy 85 ha and consist of four soil types (components), whereas individual STATSGO map units occupy 9600 ha and consist of 14 components.

In hydrologic models, the spatial resolution of input data, such as soils, land cover, and topographical information, determines the scale at which a model can accurately simulate watershed processes (FitzHugh and Mackay, 2000; Migliaccio and Chaubey, 2008). However, in modeling exercises with large domains, the gathering of data and preparation of input files may be costly and time consuming. In hydrologic modeling, the use of the hydrologic response unit (HRU) is one method used to strike a balance between input resolution and model efficiency. A HRU is an area of “homogeneous” hydrologic characteristics determined by the spatial overlay of datasets such as elevation, land use, and soil type. The use of the HRU in a hydrologic model conserves some of the spatial variation in input parameters, while reducing model complexity by lumping areas with similar hydrologic characteristics into a single unit (Nietsch et al., 2005). Within an individual HRU, the dynamics of the hydrologic processes are assumed to be small compared to the variation between HRUs (Legesse et al., 2003). This assumption is dependent partly on continuous and consistent soil data coverage to identify the most expansive soil units or “soil types”. Inconsistencies in soil coverage can artificially reduce the area represented as a certain soil type and potentially affect which soil types are included in the model. Hydrologic models using the HRU concept include the Precipitation Runoff Modeling System (PRSM) (Leavesley et al., 1983), SWAT (Arnold et al., 1998), U.S. Army Corps of Engineers Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS) (USACE-HEC, 1998), and Hydrologic Simulation Program Fortran (HSPF) (Donigian et al., 1995).

Aggregation of soil data by SSURGO MUkey may not provide the continuous, consistent soil coverage to ensure the HRU calculation produces an accurate distribution of soil physio-chemical factors. This distribution is important, as soil properties such as sand, silt, and clay percentages, bulk density, hydraulic conductivity, etc., will have a large impact on determining surface and soil water processes (Di Luzio et al., 2004; Geza and McCray, 2008). To effectively use soil survey information within a domain that spans multiple survey areas, it becomes necessary to define the term “soil type” in a way that can transcend artificial boundaries imposed by regional differences in map unit design, edge-matching errors, or variations in naming convention. Soil taxonomy (Soil Survey Staff, 1999) provides a robust and mature framework for grouping soils based on physical and chemical properties, at several levels of generalization.

The objective of this study is to refine the operational definition of “soil type” within the context of hydrologic modeling using a robust system of soil classification (Soil Taxonomy) rather than a datatbase construction (map unit). A case study using the SWAT hydrologic model of the San Joaquin River Watershed compares the new method for soil data aggregation based on soil taxonomic data contained in the SSURGO database with the typical case of using the map unit for aggregation.

MATERIALS AND METHODS

Study Site

The study site (Fig. 1) is the northern portion of the San Joaquin River Watershed located in California’s Central Valley. The watershed is bordered by the Coast Range Mountains to the west and the Sierra Nevada Foothills to the east. The total area is 14,983 km^2, with 9902 km^2 in the San Joaquin Valley, 2182 km^2 in the Coast Range, and 2899 km^2 in the Sierra Nevada Foothills. The watershed is dominantly agricultural and includes either the entire or parts of the counties of Stanislaus, Merced, Madera, San Joaquin, Mariposa, Tuolumne, San Benito, and Fresno (Fig. 1). Crops in the study area consist of fruits and nuts (38%), field crops (36%), truck, nursery, and bean crops (17%), grain crops (4%), and others (5%) (DWR, 2007). The region has a Mediterranean climate with hot, dry summers and cool, wet winters. Average rainfall is approximately 20 to 30 cm with most of the precipitation falling

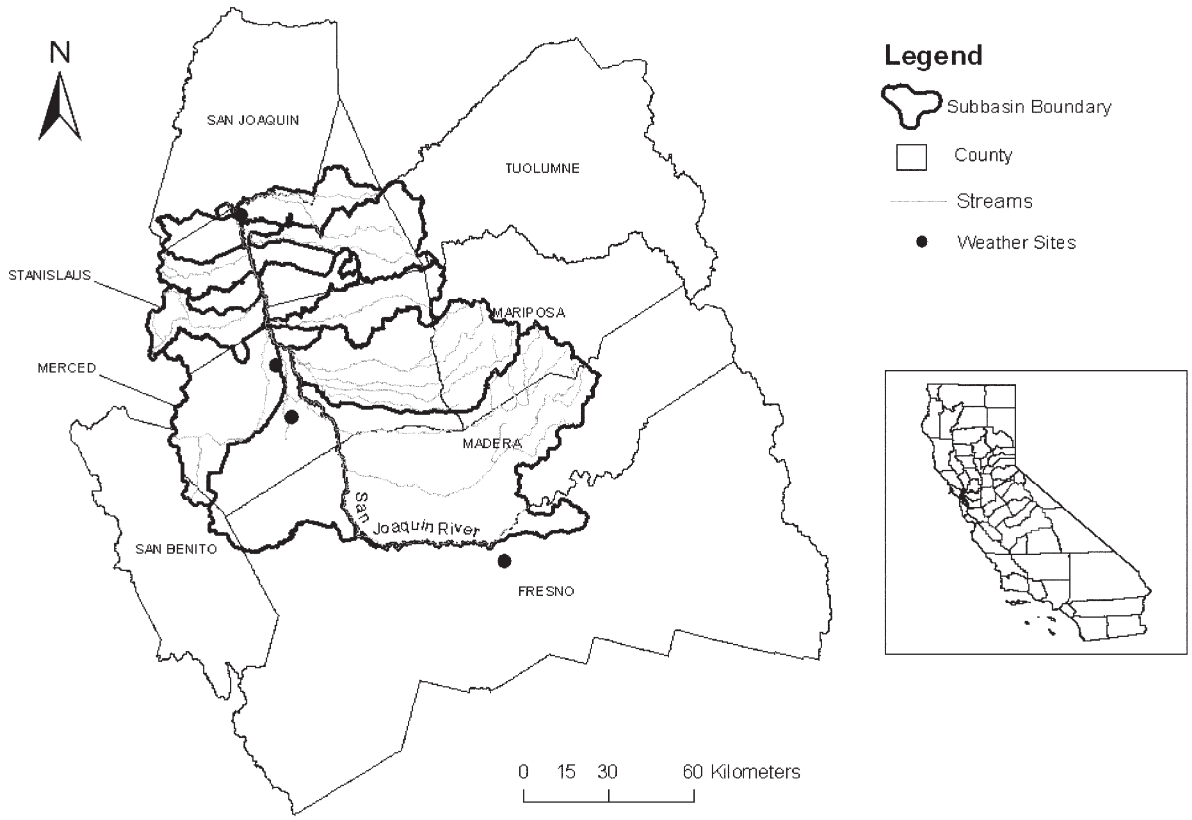

Fig. 1. Delineated subbasins of the San Joaquin River Watershed.

during the period between November and May, while precipitation between June and October is negligible. The summer months were not included in the analysis because the rainfall in the summer months is negligible and irrigation use data is not readily available. Therefore, only the rainy winter months were used in the analysis.

The soils of the San Joaquin Valley have been mapped at a scale of 1:24,000 (or finer) and released as a SSURGO certified database by the USDA-NRCS. A small region of the watershed used within our study lies within Tuolumne County, where detailed soil mapping is still in progress. Typically this hole would be filled with STATSGO data (a 1:250,000 scale soils map), however we chose to exclude this region from our analysis. Therefore, the entire spatial domain of our study made use of a seamless SSURGO database for the entire Valley and most of the surrounding foothills.

Variation in soil characteristics within the study area can be attributed to three main types of parent material: (i) east-side granitic alluvium, (ii) west-side mixed sedimentary alluvium, and (iii) basin alluvium of mixed sources. Soils to the east of the San Joaquin River typically have sandy to sandy-loam textures, with finer textures and duripans (silica-cemented horizons) on older terraces. Soils to the west of the San Joaquin River typically have loamy to clay textures, with calcic or petrocalcic horizons (calcium carbonate cemented horizons) on oldest terraces. Near the San Joaquin River, soils have formed from mixed sources with a wide range of textures. Soils in the basin floor and rim positions, along with the west-side alluvial soils, often contain high levels of dissolved salts.

The study area is dominated by Alfisols (48%), soils with an illuvial subsurface accumulation of clay, Mollisols (20%), soils with thick, organic matter enriched surface horizons and Inceptisols (19%), soils with weak soil development that account for most of the soils in upland regions. Entisols (19%) are common in current and ancestral stream channels, as well as on steep or eroded upland slopes. Vertisols, soils dominated by shrinking and swelling clay (i.e., smectite), occur in 6% of the total study area. Due to the large differences in soil properties on the east and west side of the watershed, results of the hydrologic output were divided into east and west sections depending on whether the subbasin was east or west of the San Joaquin River.

Soil Input Generation

Four different soil inputs were prepared to test our hypothesis that soil taxonomy can be a useful "soil type" identifier for aggregating soil data for use in hydrologic models. The four soil inputs include one input, Tax Soil, which was created using soil taxonomy to identify soil type and an aggregation technique outlined in Soil Profile Aggregation Algorithm. The other three soil inputs, MU Soil, Random Soil, and Reference were created using the map unit to identify soil type and aggregated, when necessary, as outlined in the Soil Profile Aggregation Algorithm section. The four soil inputs were then evaluated based on hydrologic output from a previously developed SWAT model of the San Joaquin River Watershed (Luo et al., 2008). The preparation of soil inputs to the model is described in Fig. 2. Note that the first step on the flow chart in Fig. 2 is to divide the study area into the eastern and western portions of the valley. This step was needed due to the very different soil characteristics of those two areas, and is discussed in further detail in the Statistical Analysis section. The following sections describe, in detail, the processes outlined in the flow chart.

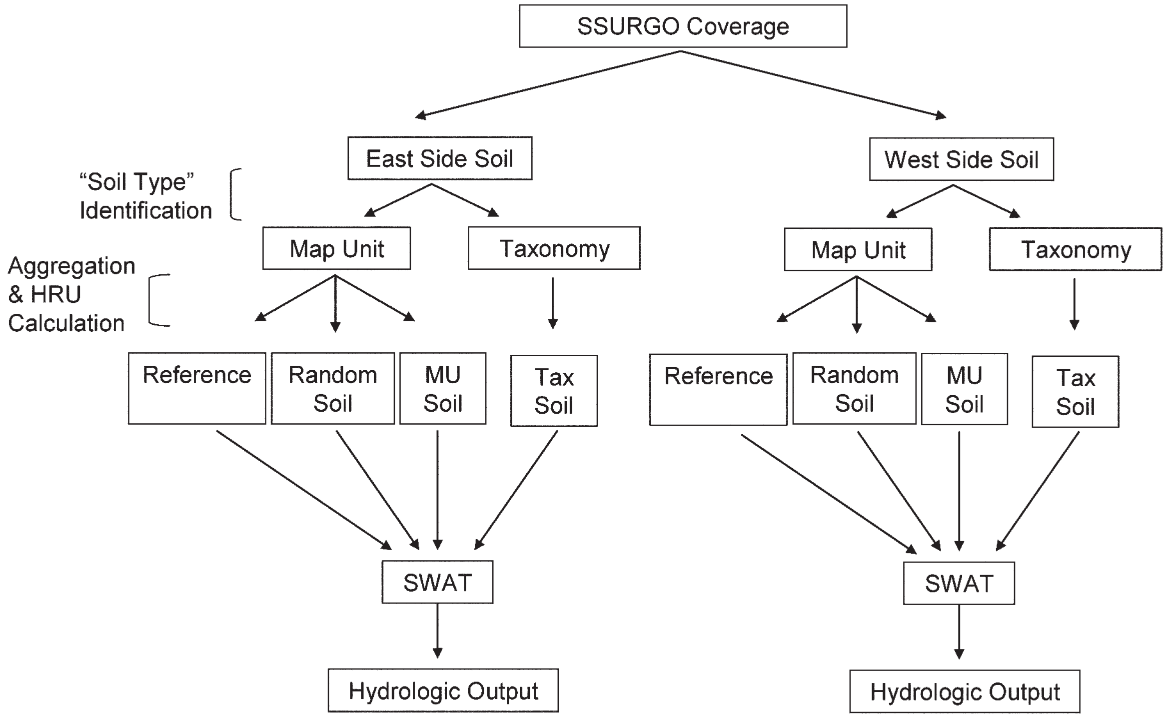

Fig. 2. Flow chart summarizing the steps of the soil aggregation and hydrologic model process.

Soil Profile Aggregation Algorithm

Distributed hydrologic models, such as SWAT, rely on gridded or polygon maps of horizon-level soil property information linked by a code such that any given "soil type" will correspond to the data for a single soil profile. In SSURGO, soil profile information (horizon texture, organic matter content, depth, etc.) is associated with soil components. Soil components which commonly occur together are grouped into map units. In the SSURGO database, map units are spatially defined, but the soil components within the map units have no spatial reference (Fig. 3). When map units are used to define soil type, an aggregation step is required to reduce the "one to many" cardinality (relationship) between soil component data and map unit polygons to a "one to one" cardinality. This process requires either the selection of a single component to represent the entire map unit (a subset-based reduction in cardinality), or a soil horizon template that is used to combine each of the component's data (an aggregation-based reduction in cardinality) into a single set of horizon-level information per map unit. Clearly, the second method (profile aggregation) is most appropriate when using a collection of map units (and their associated components) that is defined by some higher-level criteria such as taxonomic membership. Profile aggregation may be weighted according to component area so that larger components contribute most to the final "representative profile", without losing information from smaller components. In addition, the resulting representative profile contains both a measure of central tendency and variation around that tendency (Fig. 4a, 4b). All components ("major components", "minor components", and "inclusions") having associated horizon data were included in the aggregation. The entire process can be summarized in two aggregation steps which manipulate the soil data into a usable format: (i) representative soil horizon aggregation and (ii) representative soil profile aggregation.

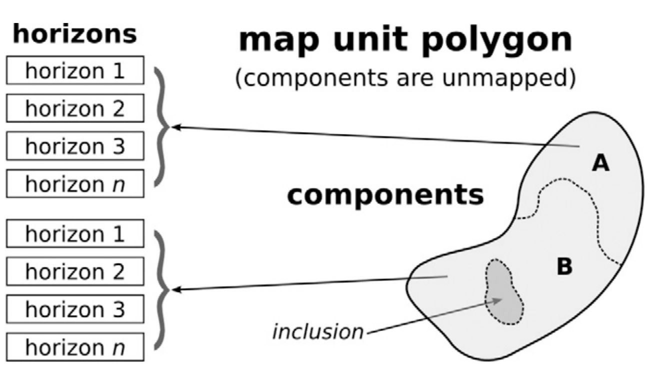

Fig. 3. Illustration of soil survey data architecture.

The first aggregation step is required to convert the collection of soil profiles, defined by the grouping strategy (map unit, great group taxonomy, etc.), into a standardized soil horizon structure (Fig. 4). The soil horizon structure used in this study is as follows: 0 to 5, 5 to 10, 10 to 15, 15 to 30, 30 to 60, 60 to 90, 90 to 150, 150 to 250 cm. Aggregation into the pre-defined soil horizon structure must be completed for each of the soil properties of interest for every soil profile (Fig. 4a). The soil properties necessary for SWAT include: percent sand, silt, and clay, bulk density, cation exchange capacity, saturated hydraulic conductivity, soil depth, water storage, organic carbon, and soil erodibility factor.

The second aggregation step is required to reduce the collection of soil profiles into a single representative soil profile with a set of depth-functions for each soil property (Fig. 4b). The second aggregation step varies slightly depending on the grouping strategy (map unit key, great group taxonomy, etc.). For the MU Soil input, representative soil profiles are derived from the collection of components within each map unit. For the Tax Soil input, representative soil profiles were derived from the collection of components associated with polygons derived from merging adjacent map unit polygons of the same great group taxa, within each subbasin. The contribution of a single component's data to a representative depth-function is weighted by the area of that component, within the study area for the MU Soil input or within the current subbasin Tax Soil input (Fig. 4).

A summary of the entire aggregation algorithm can be broken down into three steps. First, each soil profile from the SSURGO database was extracted and "segmented" into 1-cm slices. Next, the collection of segmented soil profiles defined by a grouping variable such as map unit key or combination of subbasin and great group level taxonomic units were combined, column-wise, into a ragged matrix. Columns in this matrix were padded with not available (NA) values to the depth of the deepest profile within the group, forming a rectangular matrix. The resulting matrix was partitioned, row-wise, at the standardized horizon boundaries described above. Weighted-mean values were computed within each partition and assigned to each standardized horizon. This process was repeated for each soil property used by the SWAT model. This algorithm is fully documented and publicly available in the "aqp" package for **R** (Beaudette and O'Geen, 2010). Several previous studies have demonstrated methods for associating a "conceptual soil profile" with a collection of related soil profiles via aggregation of combinations of genetic horizons forming "tiers" (Lentz and Simonson, 1987), or assigned based on statically-determined similarity to an a priori modal soil type (Carré and Girard, 2002; Carré and Jacobson, 2009). Our approach was more mechanical in nature than these studies, making no a priori assumptions regarding modal horizon or soil type.

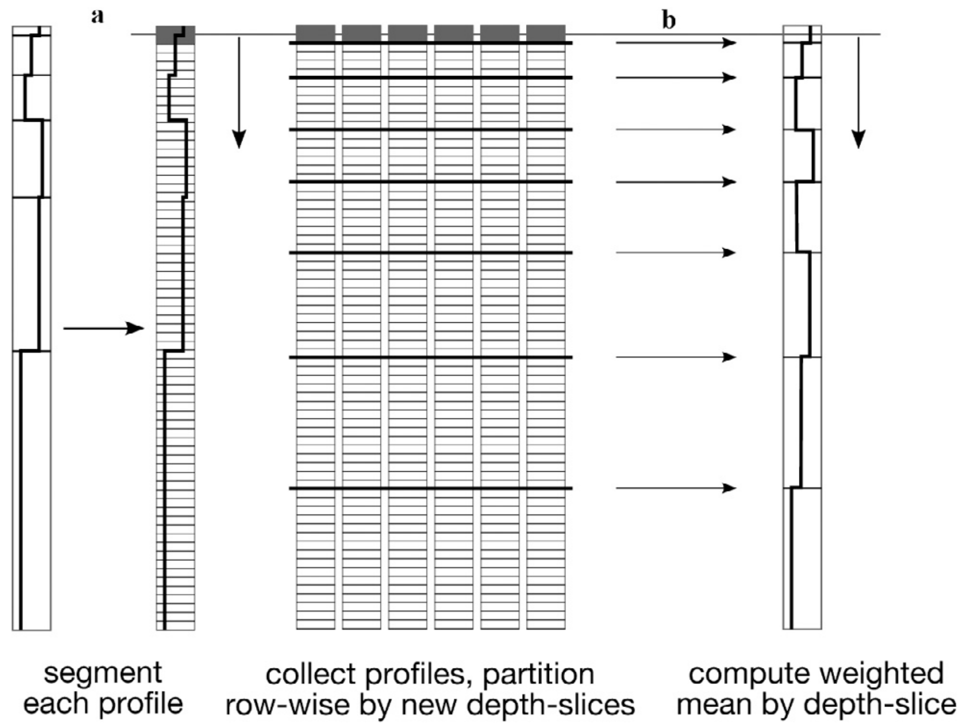

Fig. 4. Aggregation algorithm schematic. The process is outlined for a single group of profiles and single soil property. (a) Soil property depth-functions aggregated into a representative soil horizon structure. (b) Group of soil profiles aggregated into a representative soil profile, weighted by area. Profile weights are derived from the area of that profile, within the study area (map unit [MU] Soil input–aggregated at mukey level) or within the current subbasin (Tax Soil input– aggregated at the taxonomic level).

Hydrologic Response Unit Generation

Following soil data aggregation, the next step in preparing the soil inputs for the hydrologic model is HRU generation. In the preprocessing of SWAT input data, a watershed is divided into multiple subwatersheds, which are then divided into units of unique soil/land-use characteristics called HRUs. The HRUs are areas of homogeneous geomorphologic and hydrological properties which commonly occur within a watershed (Flugel, 1995). The ArcSWAT version of the SWAT model provides users with the graphic user interface tool within the ArcGIS software. The user imports land cover and soil coverages into the work space and the automated ArcSWAT tool calculates HRUs by overlaying land use and soil coverages. The calculation depends on the user specifications for land cover and soil area thresholds. For example, a specific HRU land unit may contain sandy loam and walnut orchards. Only land cover and soil types occurring at or greater than the threshold percentage are represented by HRUs. The land use and soil areas that are not above the user- defined threshold are not modeled. The land area occupied by the land use and soil type combinations below the user-defined threshold are redistributed between land use and soil type combinations above the user-defined threshold, so that 100% of the watershed is represented. Similar land use/soil types are lumped together within the subbwatershed for model simplicity and therefore do not have a spatial location within the subwatershed.

In this study, the elevation and land use data remained constant for each soil input so that the terrain characteristics remained the same. Therefore, the output of the hydrologic model depends only on differences in the soil inputs.

Soil Input

As previously stated, four soil inputs were prepared to test the value of using soil taxonomy to identify soil type. The soil inputs differ in both the method of soil type identification and the user defined threshold for determining the number of soil types used in calculating the HRUs. A low user defined threshold will include more of the mapped soil units and result in more HRUs than a high user defined threshold. These inputs are discussed in detail in the following sections and summarized in Table 1.

Reference Input. The first soil input, termed Reference, uses the entire collection of SSURGO defined map units within the watershed, and therefore is assumed to mimic actual conditions. However, use of this input for modeling applications is limited due to the size of the input files generated when considering this level of detail (Table 1).

Map Unit Soil Input. The second input, termed MU Soil, is also derived from the SSURGO soil dataset. The difference between

Table 1. Input soil dataset properties used in this study for Soil and Water Assessment Tool (SWAT) simulations.

Input name	Original soil dataset	Soil type identifier	SWAT land use threshold	Number of HRUs†	File size	Run time
					megabytes	min
Reference	SSURGO	SSURGO map units	0.01%	6842	51.5	30
MU Soil	SSURGO	SSURGO map units	3.00%	216	6.6	4
Tax Soil	SSURGO	Great Group and subbasin membership	3.00%	150	4.5	4
Random Soil	SSURGO	Randomly selected SSURGO map unit	3.00%	216	6.6	3.5

† HRU = hydrologic response unit; SSURGO = Soil Survey Geographic Database; MU = map unit.

the MU Soil input and the Reference input is that a threshold of 3% has been set for soil types, meaning that only SSURGO defined map units occupying at least 3% of the area of a subbasin are included when calculating HRUs. This approach reflects a balance between including detailed soil information and maintaining a manageable input file size.

Tax Soil Input. In the Tax Soil input, HRUs are calculated with a 3% threshold for soil type. However, instead of using the SSURGO defined MUkey as a soil type identifier, soil type was defined by a combination of great group level taxonomic membership and subbasin ID. For example, a Haploxeroll found in subbasin 12 will have a unique identifier of “Haploxeroll-12”. Several great groups in the study area are functionally similar, and were therefore merged resulting in two new composite groups: (i) Xerorthents-*, composed of Xerorthents + Xerochrepts + Haploxerepts, and (ii) Haploxererts-*, composed of Haploxererts and Chromoxererts. The assignment of representative soil profile data to collections of map unit polygons (identified by great group taxa and subbasin ID) was performed by matching greatgroup/subbasin codes associated with representative soil profile data to corresponding greatgroup/subbasin membership of map unit polygons. In the case of multi-taxa map units, a single greatgroup/subbasin code for these map units was determined using a simple rule: (i) select the most extensive greatgroup within the current map unit as representative, after computing the total component percentage as grouped by greatgroup level taxonomy, or, (ii) in the case of a tie, select a greatgroup from those within the map unit at random. Therefore, component-level data were aggregated into representative soil profiles outside the context of map units, then assigned to map unit polygons based on the above criteria.

Random Soil Input. The randomly chosen soil input, hereafter termed “Random Soil”, had the same horizontal aggregation format as the MU Soil input. However, one of the soil entries for the MU Soil input was randomly chosen and replaced all other entries in the input. Therefore, the soil input (to the SWAT model) contained a single “soil type” that was distributed across the entire study area. The soil horizon properties are found in Table 2.

Hydrologic Model

The SWAT program is a hydrologic/water quality model developed by United States Department of Agriculture-Agricultural Research Service to predict the impact of agricultural- or land-management on water, sediment, and agricultural chemical yields in watersheds (Arnold et al., 1998). The SWAT program is a continuous-time, spatially distributed model capable of simulating the hydrologic cycle and agricultural pollutant transport at daily, monthly, or annual time-steps. SWAT integrates processes of several other models, allowing for the simulation of climate, hydrology, plant growth, erosion, nutrient transport, and transformation, pesticide transport, and management practices (Nietsch et al., 2005). For this study, monthly time steps were used for the simulation time period of 1992 to 2005. The SWAT 2005/ArcSWAT version, which is coupled with ESRI’s ArcGIS version 9.3, was selected for this study.

All calculations in SWAT are based on the water balance in each HRU and updated at each time step t:

$$\mathrm{SW}_t = \mathrm{SW}_0 + \sum_{i=1}^{t}(R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw}) \qquad [1]$$

where SW_t is the final soil water content (mm H_2O), SW_0 is the initial soil water content on day i (mm H_2O), t is the time (days), R_{day} is the amount of precipitation on day i (mm H_2O), Q_{surf} is the amount of surface runoff on day i (mm H_2O), E_a is the amount of evapotranspiration on day i (mm H_2O), w_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm H_2O) and Q_{gw} is the amount of groundwater return flow on day i (mm H_2O). Flow and sediment generation is summed across all HRUs in a subwatershed and the resulting flows and sediment loads are then routed through channels to the watershed outlet. Runoff and infiltration is estimated using the physically-based Green-Ampt infiltration method (Green and Ampt, 1911). Lateral flow is simulated using a kinematic storage model for subsurface flow developed by Sloan et al. (1983). This model simulates subsurface flow in a two-dimensional cross-section along a flow path down a slope, accounting for hydraulic conductivity, slope, and soil water content. Erosion and sediment yield are estimated for each HRU with the Modified Universal Soil Loss Equation (MUSLE) (Williams, 1975). Evapotranspiration is calculated using the Penman–Monteith method. All model scenarios were left uncalibrated, as calibration may mask the differences that result from applying different soil inputs. Additionally, the uncalibrated model results show how well each dataset predicts before calibration, which would indicate

Table 2. Soil properties for the Random input.

Property	Soil layer 1	2	3	4	5	6	7	8
Sand, %	22	22	22	22	22	22	20	19
Silt, %	28	28	28	28	28	28	38	44
Clay, %	50	50	50	50	50	50	42	37
Bulk Density, g cm^{-1}	1.7	1.7	1.7	1.8	1.8	1.8	1.8	1.8
Saturated hydraulic conductivity, mm h^{-1}	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3
Layer thickness, mm	50	50	50	150	300	300	600	20

Table 3. Characteristics of Soil Survey Geographic Database (SSURGO) surveys included in this study.†

Side of Valley	Survey ID	Survey name	Publication date	Survey area	Number of Great Groups	Map units	Map units as complex percent	Mean area per map unit	Components with data	Mean area per component
				ha			%	ha		ha
Both	ca077	San Joaquin County	1992	369,361	23	186	22	1986	218	1694
East	ca632	Stanislaus County, Northern Part	2007	44,157	14	51	12	866	62	712
East	ca750	Sierra National Forest Area Parts of Fresno	1983	399,237	20	120	39	3327	209	1910
East	ca649	Mariposa County Area	1974	197,618	10	80	36	2470	109	1813
East	ca654	Eastern Fresno Area	1971	454,897	22	399	6	1140	472	964
East	ca644	Eastern Stanislaus Area	1964	190,319	20	222	5	857	243	783
East	ca651	Madera Area	1962	348,699	21	257	12	1357	335	1041
East	ca648	Merced Area	1962	269,483	18	282	5	956	304	886
West	ca653	Fresno County, Western Part	2006	533,190	25	149	17	3578	224	2380
West	ca642	Stanislaus County, Western Part	2002	158,159	15	106	45	1492	170	930
West	ca647	Merced County, Western Part	1990	241,038	17	189	28	1275	254	949
West	ca069	San Benito County	1969	359,918	16	217	18	1659	338	1065

† All survey locations are in within the state of California.

the amount of effort needed to calibrate the model (Geza and McCray, 2008).

Data Collection and Analysis

The SWAT input parameter values such as topography, landscape, and weather data were compiled using databases from various state and federal governmental agencies. The 30-m resolution Digital Elevation Models (DEMs) and 1:100,000 scale stream network data from the National Hydrography Dataset (NHD) were obtained from USGS. The SSURGO data was obtained from the NRCS. The SSURGO soil coverage for the watershed includes portions of 13 soil survey areas (Table 3). Landuse data was obtained from the California Department of Water Resources (DWR) during 1996 to 2004 under the assumption that agricultural land use has not changed since the survey was completed. Hourly precipitation and daily minimum and maximum temperature were retrieved from four California Irrigation Management Information System (CIMIS) weather stations in the study area (Fig. 1).

Statistical Analysis

To evaluate strategies for HRU generation, aggregate soil properties were computed from the collection of components associated with the Tax Soil and MU Soil inputs, and compared with the Reference input. The Reference input was based only on subsets of aggregate soil properties defined by HRU strategy, and did not use the previously mentioned soil profile aggregation algorithm. Aggregate representations of soil properties used by the SWAT model (i.e., entire soil profiles), subset by input, were compared using weighted means within the framework of a linear model in the **R** statistical program (Webster and Oliver, 1990; R Development Core Team, 2010). Map unit polygon areas (original SSURGO data) within each side of the valley were used as weights in the comparison. All properties (except soil depth, water storage, and organic carbon) were aggregated to the component-level by computing a horizon thickness weighted average (R Development Core Team, 2010). Soil depth, water storage, and organic carbon values were summed within each component, yielding component-level totals. Organic carbon concentrations were converted into quantities according to rock fragment, bulk density, and horizon thickness, and then summed, to make between-profile comparisons of organic carbon more resistant to differences in soil depth. Component-level soil properties were pooled according to their position with respect to the San Joaquin River, into "East-Side Soils" and "West-Side Soils". Standard error for the Reference dataset and the other soil inputs were computed by pooling values by "side of the valley" and input. Note that these are the standard errors associated with the collection of components defined by our grouping criteria– not the standard errors of any single component's data. The division of the study area into an East-Side and West-Side was necessary due to the differing number of HRUs for each soil input. While the number and size of the subbasins remained the same for all inputs, the number of HRUs differed. Several previous studies have addressed the effects of HRU size on SWAT output. Arnold et al. (1998) found that SWAT produced similar flow results for one scenario where one HRU was chosen to represent the entire watershed compared to another scenario where 155 HRUs were delineated for the watershed. Conversely, Chen and Mackay (2004) found that different levels of watershed partitioning introduce almost half the variability in the modeled sediment generation. Therefore, it is unclear whether or not the comparison of different populations of HRUs in this study was a possible source of bias in the results. However, because the goal of this study was to compare soil datasets with different spatial resolutions, the number of HRUs will inherently be different for each soil dataset.

Early testing of the results indicated that there was a large difference between the east and west side of the watershed and not as much variation between HRUs within each side of the watershed. To address this, a similar approach to the soil property aggregation technique previously discussed was taken. For example, a surface runoff value for January on the east side is the total surface runoff for all subbasins (and therefore HRUs) on the east side. The weighted-mean of the MU Soil and Tax Soil inputs were compared with the weighed-mean of the Reference input, for each side of the study area. Weights were computed for each component by multiplying each component's area fraction (i.e., the component percentage) by the area extent of the parent map unit, within each side of the study area. Because hydrologic group is categorical data, the proportions of A, B, C, and D type hydrologic group (SCS, 1984) were computed for each side of the study region, based on the subset of total map units defined by HRU input (Reference, MU Soil, and Tax Soil). Proportions were determined by first computing the total area of each group within each side of the study region, and then dividing this value by the total area within each side of the study region.

Estimations for soil water content, surface runoff, lateral flow, and sediment yield from each HRU delineation (input) method were compared to the Reference input. For the hydrologic output, two

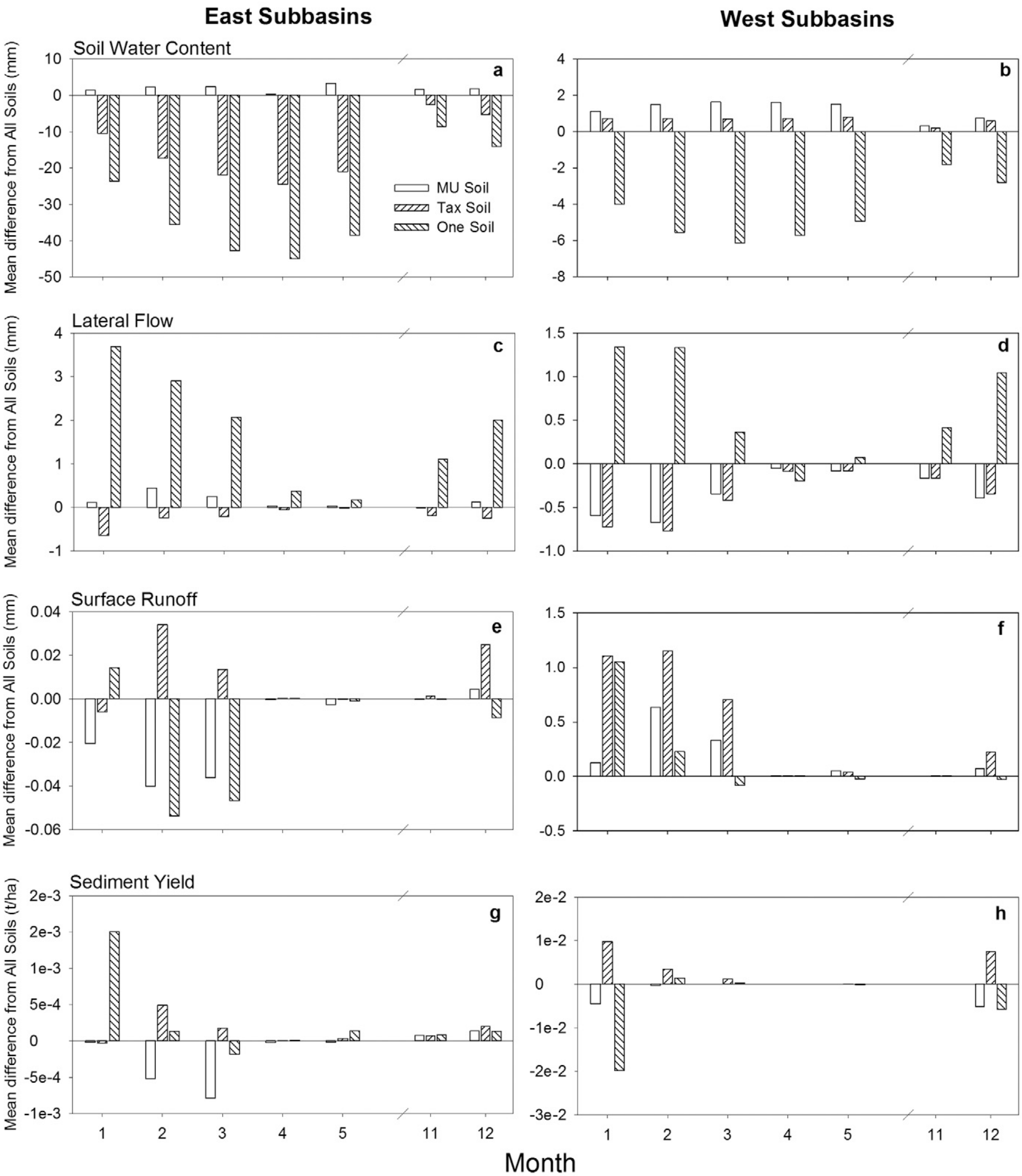

Fig. 5. Average rainy season monthly hydrologic output. The values are presented as the difference in means when compared to the Reference input.

statistical summaries were performed: monthly and seasonal statistics. The January monthly average lateral flow, for example, is calculated by taking the 14-yr average of simulated total lateral flow in the month of January (Fig. 5c, 5d). For the seasonal statistical analysis, the rainy season months (as defined in Study Site) were averaged to obtain a rainy season mean value, which is used in the statistical analysis of the 14 yr period (See Table 4). Thus, there were 14 samples for both the monthly and seasonal analysis. Results were also summarized based on soil water processes (soil water content and lateral flow) and surface processes (surface runoff and sediment yield).

The analysis of each hydrologic output includes several statistical parameters: mean, standard deviation, mean difference (MD), and the root mean standard difference (RMSD) (Eq. [2–3]. The MD and RMSD decrease with increasing accuracy compared to the Reference simulation. The RMSD expresses the degree of which the simulated values differ from the Reference value. The equations for MD and RMSD are expressed as

$$\mathrm{MD}=\frac{1}{n}\sum_{i=1}^{n}[\mathrm{Sim}^{*}\text{-}\mathrm{Sim}_{\mathrm{ref}}] \qquad [2]$$

$$\mathrm{RMSD}=\left\{\frac{1}{n}\sum_{i=1}^{n}[\mathrm{Sim}^{*}\text{-}\mathrm{Sim}_{\mathrm{ref}}]^{2}\right\}^{0.5} \qquad [3]$$

where n is the number of samples, Sim^* is the simulation result from the soil aggregation technique (MU Soil, All Soil, Random Soil) and Sim_{ref} is the simulation result from the Reference soil dataset. The Mann–Whitney Rank Sum test ($P < 0.05$, two-sided) was used to compare the soil datasets since the hydrologic outputs exhibited non-normal distributions (Mann and Whitney, 1947). The Mann–Whitney Rank Sum test is based on the concept that if two groups come from the same distributions, the sum of the ranks of the values should be somewhat equally distributed between the two.

RESULTS

SSURGO Aggregation Method

The area of map unit polygon collections resulting from the Tax Soil aggregation approach averaged 330 ha, a size between that of the SSURGO (85 ha) and STATSGO (9650 ha) databases from California. It is worth noting that, direct aggregation of SSURGO data (as opposed to the use of STATSGO data) makes use of the most up-to-date soil property information for the additional land that has been surveyed since 1994. Aggregate (weighted-mean) representations of soil properties had minor differences between inputs (Table 5). Within the east side of the study area, the Tax Soil input (for HRU generation) was not significantly different from the Reference input (Table 5).

Table 4. Seasonal hydrologic output of the San Joaquin River Watershed Soil and Water Assessment Tool (SWAT) simulations.

	Reference†	MU soil	Tax soil	Random	Reference	MU soil	Tax Soil	Random
	Soil water processes							
	Soil water, mm				Lateral flow, mm			
East San Joaquin River Watershed Subbasins								
Mean	68.4	66.5	83.2	98.1	2.2	2.1	2.5	0.5
SD	42.2	44.6	54.8	68.4	3.4	3.6	4.1	0.6
MD‡	–	–1.9	14.7	29.7	–	–0.13	0.2	–1.8
RMSD	–	9.9	25.2	45.3	–	1.2	1.4	3.5
Mann–Whitney Significance			*	*		*		*
West San Joaquin River Watershed Subbasins								
Mean	59.6	51.4	55.3	89.9	7.3	9.5	9.8	3.0
SD	41.7	40.7	44.6	60.4	11.4	15.2	16.0	3.9
MD	–	–8.2	–4.3	30.3	–	2.3	2.5	–4.3
RMSD	–	15.7	13.5	41.2	–	5.4	6.3	10.1
Mann–Whitney Significance				*				*
	Surface water processes							
	Surface runoff, mm				Sediment yield, t ha^{-1}			
East San Joaquin River Watershed Subbasins								
Mean	0.5	0.6	0.4	0.6	5.3E-03	6.4E-03	4.4E-03	3.5E-03
SD	4.2	5.1	4.0	5.6	4.6E-02	6.8E-02	5.9E-02	3.6E-02
MD	–	0.1	–0.1	0.1	–	1.1E-03	–9.0E-04	–1.8E-03
RMSD	–	1.3	0.7	3.6	–	3.1E-02	2.3E-02	4.1E-02
Mann–Whitney Significance		*	*	*			*	*
West San Joaquin River Watershed Subbasins								
Mean	0.8	0.6	0.3	0.6	3.7E-02	4.7E-02	1.6E-02	6.1E-02
SD	5.0	4.7	2.3	4.7	6.9E-01	9.8E-01	3.1E-01	1.5E+ 00
MD	–	–0.2	–0.5	–0.2	–	1.0E-02	–2.1E-02	2.4E-02
RMSD	–	0.9	3.0	3.1	–	2.9E-01	3.9E-01	8.9E-01
Mann–Whitney Significance		*	*	*		*	*	*

* Statistically different at $P < 0.05$ using the Mann–Whitney significance test.

† Reference = non-aggregated soils input; MU soil = aggregated at map unit key level; Tax Soil = aggregated at taxonomic level.

‡ MD = mean difference; RMSD = Root Mean Standard Difference.

Table 5. Differences in area weighted mean soil property values for the MU Soil (aggregated at map unit MUkey level) and Tax Soil (aggregated at the taxonomic level) inputs in reference to the Reference input (no aggregation) for the San Joaquin River watershed. Weighted mean soil property values for the Reference input are included for scale.

	San Joaquin River Watershed-East Side			San Joaquin River Watershed-West Side		
Parameter	Ref. wt. mean [N = 2055]†	Wt. mean diff. MU Soil–Ref. [N = 209]	Wt. mean diff. tax soil–Ref. [N = 1674]	Ref. wt. mean [N = 1180]	Wt. mean diff. MU Soil–Ref. [N = 379]	Wt. mean diff. Tax Soil–Ref. [N = 883]
Sand, %	56.9	5.21*	0.18	37.94	0.09	1.04
SE	0.43	0.76	0.62	0.45	0.72	0.67
Silt, %	24.39	−1.57*	0.25	31.76	0.66	0.49
SE	0.26	0.46	0.37	0.25	0.4	0.38
Clay, %	18.71	−3.65*	−0.43	30.3	−0.75	−1.52*
SE	0.24	0.43	0.35	0.36	0.58	0.54
Bulk density, g cm^{-3}	1.66	0	0	1.69	0	0
SE	0	0	0	0	0	0
Cation exchange capacity, cmol (+)kg^{-1} soil	12.09	−2.64*	−0.48	19.93	−0.02	−1*
SE	0.18	0.32	0.26	0.24	0.38	0.36
Log Ksat‡, mm h^{-1}	1.54	0.24*	0.01	1.05	0.1*	0.09*
SE	0.01	0.03	0.02	0.02	0.03	0.03
Soil depth, cm	92.41	2.12	−0.53	108.85	−7.32*	−3.3
SE	1.12	2	1.62	1.6	2.56	2.38
Water storage, cm	11.07	−0.48	−0.05	15.26	−0.33	−0.1
SEr	0.15	0.26	0.21	0.27	0.44	0.4
Organic carbon, kg m^{-2}	456.56	−25.51	−8.39	780.47	−15.05	−30.42
SE	6.16	11	8.92	16.78	26.92	25.01
K Factor§	0.32	−0.02*	0	0.35	0	0
SE	0	0	0	0	0	0

* Statistically different ($P < 0.05$).

† Reference = non-aggregated soils input; wt. = weight; MU Soil = aggregated at map unit key level; Tax Soil = aggregated at taxonomic level.

‡ Ksat = saturated hydraulic conductivity.

§ K factor = Universal Soil Loss Equation soil erodibility factor.

Soils from the MU Soil input had significant differences when compared to the Reference input in terms of: sand content (+5.21%), silt content (−1.57%), clay content (−3.65%), cation exchange capacity (−2.64 cmol (+)/kg soil), saturated hydraulic conductivity (log (mm/h)), and K factor (+0.32). Within the west side of the study area, soils selected according to taxonomy had significant differences when compared to the Reference input in terms of: clay content (−1.52%), cation exchange capacity (−1.00 cmol (+)/kg soil), and saturated hydraulic conductivity [+0.09 log (mm/h)]. Soils from the MU Soil input had significant differences when compared to the Reference input in terms of: saturated hydraulic conductivity [+0.10 log (mm/h)] and soil depth (−7.32 cm). Despite the statistical significance associated with these differences (due in part to the large number of components used within the comparison), at the HRU scale the practical significance of these differences is slight. However, the cumulative effect of these differences across the entire San Joaquin watershed can have practical impacts on hydrological model output.

Differences between proportions of hydrologic group were generally minor within all HRU inputs (Table 6), with the greatest variability on the east side of the San Joaquin River. Proportions of each hydrologic group associated with the Tax Soil input were in closest agreement with the Reference input on the east side of the study area. While the hydrologic grouping is not an important factor in this study due to the use of the Green-Ampt infiltration method, many other hydrologic models rely on the hydrologic group for estimates of runoff.

Hydrologic Response Unit Generation

The soil threshold percentage of 0.01% for the Reference dataset led to the generation of 5003 HRUs for the east side of the watershed and 1839 HRUs for the west side of the watershed. The soil threshold percentage of 3% lead to the generation of 89, 79, and 89 HRUs for the MU Soil, Tax Soil, and Random datasets for the east side and 127, 71, and 127 for the west side, respectively. The HRU total for the MU Soil and Random are identical because the Random SSURGO input file was based on the MU Soil input with exception that every soil profile was changed to the profile presented in Table 2.

Soil Database Size and Soil and Water Assessment Tool Model Run Time

The SWAT model run times and soil input database sizes were affected by the method used for soil type identification and soil aggregation. The SWAT model run times using the Tax Soil and MU Soil inputs were approximately the same at 4 min per run, while the Reference dataset run times were approximately 30 min per SWAT model run. If extrapolated out for a model sensitivity analysis (~1000 model runs), using the Tax and

Table 6. Comparison of hydrologic group (SCS, 1984) distribution by watershed side and soil input. "East" and "West" refer to the east and west side of the San Joaquin River watershed, respectively.

Side of San Joaquin Watershed	Soil input	Hydrologic group				
		A	B	C	C/D	D
East	reference†	7.6	29.7	26.7	0.0	36.0
East	MU soil	12.3	31.5	22.9	0.0	33.3
East	Tax Soil	7.7	30.7	25.3	0.0	36.3
West	reference	1.1	16.4	27.6	0.2	54.8
West	MU soil	0.0	17.2	30.4	0.0	52.4
West	Tax Soil	0.7	19.4	28.9	0.0	51.0

† Reference = non-aggregated soils input; MU soil = aggregated at map unit key level; Tax Soil = aggregated at taxonomic level.

MU Soil inputs would amount to nearly 3 d of model runs. Comparatively, the sensitivity analysis for the Reference soil input would take nearly 21 d.

The total San Joaquin River Watershed soil database size, which was used as the SWAT model input, differed for each soil input dataset. At 4.5 megabytes, the Tax Soil database had the smallest soil database. The MU Soil database was 6.6 megabytes (1.5 times larger than Tax Soil) and the Reference database was 51.5 megabytes (11 times larger than Tax Soil). While these numbers may be small in terms of modern-age computing, larger modeled areas will lead to much larger databases.

Hydrologic Outputs

The SWAT hydrologic outputs using the MU Soil, Tax Soil, and Random input simulations showed no statistically significant patterns. However, in general, the MU Soil and Tax Soil inputs simulated statistically similar hydrologic output to the Reference input simulation (Table 5). In fact, for the estimates of soil water process (soil water content and lateral flow) only the estimate of lateral flow using the MU Soil input in the eastern subbasins was significantly different than Reference dataset output (Table 4). For surface hydrologic processes (surface runoff and sediment yield), only one case, the MU Soil input, simulated results that were not significantly different to the reference values (Table 4). In all cases, simulating hydrologic process using the Random Dataset resulted in significantly different estimates of output than the reference simulation Table 4.

Soil Water Content

Generally, soil water content was best predicted using the MU Soil input for the eastern subbasins and Tax Soil for the western subbasins as compared to the Reference input (Table 4, Fig. 5b). The MU Soil hydrologic output led to a statistically similar soil water output as the Reference input, while using the Tax Soil input led to a statistically different soil water output. For eastern subbasins, simulations with the MU Soil input led to an under prediction of soil water content for all months compared to the reference simulation (Fig. 5a). Using the Tax Soil and Random inputs led to an over prediction compared to the reference simulation for all months in eastern subbasins (Fig. 5a). For western subbasins, the MU Soil and Tax Soil inputs predicted statistically similar outputs to the reference simulation (Table 4).

Lateral Flow

Based on the MD and RMSD statistics, the simulation using the MU Soil dataset most closely replicated the lateral flow output from the reference simulation for both sides of the watershed (Table 4, Fig. 5c, 5d). The Tax Soil input, however, produced comparable results and was also not significantly different than the reference simulation for both sides of the watershed (Table 4). Although the MD and RMSD statistics showed that lateral flow for the MU Soil input was closer to the reference output than Tax Soil input for eastern and western subbasins, the Mann–Whitney Significance test indicated that output from MU Soil simulations was significantly different than output from the reference simulation in eastern subbasins (Table 4). This may suggest that extreme events may not be satisfactorily simulated for eastern subbasins when using the MU Soil input. Using the Random input under predicted lateral flow compared to the reference values for both sides of the watershed and for all months (Fig. 5c, 5d).

Surface Runoff

The MU Soil, Tax Soil, and Random inputs resulted in statistically different surface runoff amounts compared to the output from the reference simulation (Table 4). Based on MD and RMSD statistics, using the Tax Soil dataset resulted in a better prediction of surface runoff than MU Soil input for eastern subbasins, while simulations with the MU Soil dataset produced better predictions in western subbasins when compared to the reference simulation. The Random input resulted in an over prediction for eastern subbasins and an under prediction for western subbasins compared to the reference simulation. For all input datasets, the largest differences in surface runoff occurred in January, February, and March (Fig. 5e, 5f).

Sediment Yield

Only model simulations run using the MU Soil dataset produced statistically similar estimate of sediment yield to the reference simulation, and only for the eastern subbasins (Table 4). Using the MU Soil input resulted in an over prediction of sediment yield for eastern and western subbasins compared to the reference simulation with the largest differences occurring in February and March for eastern subbasins and December and January for western subbasins (Fig. 5g, 5h). The Tax Soil input resulted in an under prediction for both sides of the watershed and for all months compared to the reference simulation (Fig.

5 g, 5h). Based on the MD and RMSD statistics, the MU Soil input resulted in a better sediment yield prediction for the western subbasins, while using Tax Soil resulted in estimates closer to reference simulation for the eastern subbasins. Using the Random dataset resulted in an under prediction for eastern subbasins and an over prediction for western subbasins compared to the reference simulation, with the largest difference occurring in January (Fig. 5g, 5h).

DISCUSSION

Spatial Patterns in Aggregate Soil Properties Defined by Hydrologic Reponse Unit Input

The advantages of the new soil aggregation technique based on taxonomy presented in this study are: (i) the ability to aggregate soil data across soil survey boundaries and (ii) a more representative HRU delineation for hydrologic modeling purposes. Aggregate soil properties, and hydrologic group proportions, defined by the Tax Soil input appear to be in better agreement with the Reference input in eastern subbasins. This may be partially explained by the wealth of studies conducted in this region, which has led to a greater degree of scrutiny of the soils when mapping (1600 ha per map unit on the east side as compared to 2000 ha per map unit on the west side). In addition to having more map units per unit area, surveys on the east side of the watershed contain fewer (map unit) complexes (16%) than surveys on the west side of the watershed (27%). Surveys on both sides of the watershed contained approximately the same number (18) of distinct great groups (Table 3).

Survey Vintage and Edge-Matching Issues

Soil survey data that overlapped with our region of interest varied in age, with the oldest publication dates (1960–1980) occurring on the Valley floor and low foothills of the east side of the San Joaquin River, and the most recent publication dates (1980–2007) occurring on west side of the San Joaquin River and in the Sierra Nevada Mountains.

Although the NRCS has spent considerable effort toward a harmonization of map units across survey area boundaries, differences in map unit composition remain. For example, a map unit in one survey area may contain a single component, while on the other side of the survey boundary the corresponding map unit may contain several components. Even though the two map units may contain components with identical taxonomic structure, the presence of several components can cause an artificial split when there are ties between component percentages (i.e., a random selection must be made to assign a single taxonomic group to the entire map unit), or when the largest component does not match. These differences vary according to survey age and style, and can result in artificial splits even when soils are grouped according to taxonomy. There were no clear patterns between model results and the publication date of the soil surveys in this region.

Despite differences in mapping style across survey boundaries, the use of taxonomic group for HRU generation will always be more likely to account for edge effects when compared to HRU generation based on MUkey. This is because taxonomic coherence between map units from adjacent surveys is always a possibility, whereas MUkey (a database construct was never meant as surrogate for "soil type") will always differ across survey boundaries. Within our study area there were a total of 1460 map unit polygon interfaces at survey boundaries. Of these 1460 cases, our taxonomic definition of soil type (for HRU generation) correctly accounted for 41% (600) of these cases. An additional 164 interfaces could have been accounted for using taxonomic HRU generation criteria and manual selection of representative components on either side of the survey boundary.

Effect of Soil Parameter Values and Distribution on Hydrologic Output

For brevity, the hydrologic output from MU Soil and Tax Soil inputs will be explored in the discussion. The Reference and Random inputs are excluded as they serve primarily as sensitivity end-member examples. The use of the Reference dataset in a hydrological model is not realistic, as computational efficiency is low. For example, a sensitivity analysis performed on hydrologic parameters required hundreds of runs amounting for over 3 mo of run time.

Due to the large number of soil parameters being aggregated, it was not possible to single out the influence of one single parameter on hydrologic output. Also, it was not the goal of the project to determine the influence of one single parameter, but rather, to determine the overall effect from the new aggregation technique. Therefore, we summarize what is thought to be the most important changes in soil properties and discuss them in respect to basic soil hydrology principles.

In SWAT, the amount of water infiltrated during a storm or irrigation event is dependent on percent clay, percent sand, bulk density, and saturated hydraulic conductivity. In eastern subbasins, the mean difference between the Tax Soil input and the Reference input was less than the difference between MU Soil input and Reference input. This is most likely due to the fact that the majority of relevant soil parameters in the Tax Soil input were statistically similar to the Reference input, whereas the MU Soil input had a greater number of differences (Table 5). For western subbasins, both the MU Soil and Tax Soil inputs simulated less runoff than the Reference input. This is likely attributed to the under-representation of clay and over-representation of sand for the MU Soil and Tax Soil inputs.

The SWAT soil water content is calculated for each HRU using Eq. [1]. Precipitation and evapotranspiration values were the same for each soil input, and therefore, soil water content for each time step is a function of the redistribution of infiltrated water as lateral flow, percolation, groundwater return flow, and initial soil water content for the time-step. The redistribution of infiltrated water occurs as continuous movement of water through the soil profile until no water is available at the soil surface. Redistribution ceases when water content throughout the entire soil profile is uniform. Downward flow or percolation occurs when field capacity of a soil layer is reached and the layer below is not saturated. Saturated hydraulic conductivity of the soil layer governs flow rate.

Though all soil water simulations are statistically similar (Table 4) to the Reference input, the mean difference between the Tax Soils and Reference inputs is greatest for the eastern subbasins. Differences between soil inputs can likely be attributed to differences in soil depth, slope, and soil properties after HRU delineation. For example, after the HRU calculations are performed in SWAT, the area weighted average soil depths for the Reference, MU Soil, and Tax Soil inputs in eastern subbasins are 1270, 1200, and 1700 mm, respectively. Depending on soil properties, a deeper soil profile will allow more water to be stored, which would lead to differences in soil water processes. The SWAT uses slope, slope length and saturated hydraulic conductivity to calculate lateral flow in the soil. For the MU Soil and Tax Soil inputs, slope and saturated hydraulic conductivity for eastern and western subbasins were higher than those for the Reference input. These elevated values are the most likely explanation for the increase in average lateral flow for all scenarios except the MU Soil input for eastern subbasins. For the MU Soil input in eastern subbasins, the increase in surface runoff resulted from reduced infiltration into the soil profile and therefore, a decrease in the amount of lateral flow.

Sediment yield in SWAT is based on the MUSLE and is a function of rainfall volume, surface runoff, the USLE C, P, and K factors, slope, slope length, and percent rock in the surface soil horizon. The Pearson correlation coefficient at $P < 0.05$ was calculated to assess the relationship between changes in surface runoff and sediment yield, where a high Pearson correlation coefficient is $r > 0.75$ and a moderate correlation is $0.5 > r < 0.75$. In all but one case, the mean difference in sediment yield when comparing the MU Soil and Tax Soil inputs to the Reference input is highly or moderately correlated to the mean difference in surface runoff. The one scenario where sediment yield estimates were not correlated with surface runoff was the MU Soil input for the western subbasins ($r = -0.18$). The most likely explanation for this discrepancy is that the HRU calculations on the west side include a larger percentage of low sediment yield land use in the rangeland and forest categories. These differences in land use coupled with a higher percentage of organic carbon in soils of western subbasins (Table 5) led to an overall lower sediment yield despite the increase in surface runoff.

The San Joaquin River Watershed is a highly managed watershed located in one of the most fertile regions in the world. Intensive agriculture increases the difficulty of simulating the region with a watershed model due to land leveling, irrigation diversions, and scheduled dam releases. Using a weighted average, the eastern and western subbasins have slopes of 0.04 and 0.12 m/m, respectively. The higher slopes of western subbasins are due to Coastal Range Mountains in the western edge of the watershed. Sierra Nevada Mountains and nearly all of the foothills are excluded from eastern subbasins, because the eastern side of the watershed is bound by reservoirs (Fig. 1). The low slope values combined with coarser textures result in less surface runoff, resulting in more water stored in the soil profile or lost as deep percolation. This is particularly important because research has called for the improvement of the over simplified soil water and groundwater routines in SWAT (e.g., Gassman et al., 2007; Kim et al., 2008).

A limitation of this study is the comparison between soil datasets instead of observed hydrologic data such as surface runoff and soil water content. Future work is needed to test the aggregation method in different climates, topographies, land management scenarios and at different spatial scales. Testing the method on additional sites may reveal different sensitivities to changes in soil parameters and aggregation than in the San Joaquin River Watershed. This method should also be applied to hydrologic models other than SWAT, such as PRSM and HEC-HMS.

CONCLUSIONS

The comparison of physical phenomenon at the regional scale requires the seamless aggregation of smaller scale datasets. This paper presents one such aggregation method for SSURGO soil datasets based on soil taxonomic information contained in the SSURGO database. Aggregating by soil taxonomic classifications reduced edge matching errors between soil survey coverages by 41% and the depth-slicing algorithm (Beaudette and O'Geen, 2010) referenced in this study provides a time-saving method for aggregating SSURGO data. Based on statistical comparisons, the Tax Soil aggregation technique produced model output comparable to the fully detailed, restrictively large SSURGO dataset (Reference input). By aggregating soils based on a single continuous convention across an entire watershed, the taxonomic aggregation method is a more representative method of HRU delineation at the watershed scale, one that reflects soil landscapes instead of dissimilar map units. Results indicate that the Tax Soil input produced statistically similar results for soil water content and lateral flow throughout the watershed when compared to the Reference input, while the results produced by the MU Soil input was statistically similar to the Reference input except for lateral flow on the East side (Table 4). The Tax Soil input did not produce statistically similar results to the Reference input for surface runoff and sediment yield. The same is true for MU Soil input, except for the East side sediment yield, for which the resulting output was statistically similar to the All Soils input (Table 4). The absolute mean difference values for the statistically different hydrologic outputs, however, were minimal (i.e., 0.5 mm for surface runoff, and 0.02 t/ha for sediment yield). Slight variations in soil properties, slope, and soil depths are the most likely reason for the differences in hydrologic output between the different soil inputs. Further validation of the soil taxonomy aggregation method for hydrologic modeling is needed for areas with different climates, land uses, and soils. When applying hydrologic models to large regions the traditional approach to aggregate SSURGO data using MUkey can be problematic when map unit discrepancies exist across soil survey areas. The Tax Soil aggregation technique offers the potential to group soil properties in an efficient and accurate manner that reflects dominant soil landscapes of a region.

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