Application of the Soil Water Assessment Tool in a Tropical Agricultural Catchment of the Panama Canal Watershed: Implications for its use in watershed management activities

Jordan Oestreicher
Department of Bioresource Engineering
McGill University, Montreal
July, 2008

A thesis submitted to McGill University in partial fulfilment of the requirements of the degree of Master of Science, Neotropical Environmental Option

Arrange whatever pieces come your way.

- Virginia Woolf

Abstract

The Panama Canal Watershed (PCW) provides water to operate the Canal, generate hydroelectricity, and supply water provisions to the local and metropolitan populations. With a maxed-out water budget, however, this region has little room to accommodate the possible effects of unsustainable land-use changes or of climate change, both of which threaten to alter water flows and timings. On the other hand, the water storage capacity of the canal reservoirs, necessary for water use during the dry season deficit, is compromised by sedimentation – the result of erosion and landslides on mismanaged lands. Given this context, tools must be developed to support conservation and sustainable resource use planning, watershed management activities, and risk forecasting. The Soil and Water Assessment Tool (SWAT), a physically based semi-distributed simulation watershed model, is an instrument that meets these criteria.

To assess the ability of SWAT application for use in the context of the PCW, the model was calibrated and validated for streamflow and sediment yield over a three year period (2004 – 2006) in the 75 km^2 pilot study area of the Caño Quebrado River subbasin of the PCW, an area of burgeoning pineapple farms and with a history of cattle ranching. The model demonstrated exceptional performance for weekly average simulated streamflow and baseflow (all Nash Sutcliffe coefficients > 0.76 except for the baseflow validation period), generated little significant error, and demonstrated highly accurate predictions of annual cumulative water yield. Although SWAT was also able to simulate cumulative sediment yields with acceptable precision, the model was a poor predictor of monthly average sediment yield (calibration Nash Sutcliffe coefficient = 0.48). A qualitative and quantitative sensitivity analysis reveals that this is likely owing to the compound effects of a number of imprecise input parameters and data uncertainties, namely apropos the Modified Universal Soil Loss Equation (MUSLE) parameters for pineapple crops and pasture lands, the resolution and the reliability of the soil data used in this study, and the inability of SWAT to adequately model pineapple plant cover. Overall, this study illustrates that SWAT could potentially be a beneficial support tool for use in the PCW; however issues of data scarcity in the area will need to be resolved, including that of soil survey data, the spatial and temporal representativeness of streamflow and sediment yield field data, and estimates for MUSLE parameters. Modifications to the model framework for the groundwater and plant growth model components would also enhance prediction accuracy.

Résumé

Le Basin versant du Canal de Panama (BCP) fournit l'eau nécessaire pour le bon fonctionnement du Canal, pour générer de l'hydro-électricité et pour offrir de l'eau potable aux populations locales et métropolitaines. Avec un budget d'eau serré, la région a peu de moyens pour s'adapter aux effets possibles des changements d'utilisation de terre ou les effets prévus par les changements climatiques menaçant de changer les quantités et les chronométrages de l'écoulement d'eau. Par ailleurs, la capacité de stockage des réservoirs du canal, nécessaire pour l'utilisation d'eau pendant la saison sec, est compromise par la sédimentation produite principalement par l'érosion et les glissements, conséquences des terrains gérés de façon non-durable. Dans ce contexte, des outils s'avèrent indispensables afin de mieux conserver et planifier l'utilisation des ressources naturelles, ainsi que les activités de gestion du basin. L'un des ces outils est le model Soil and Water Assessement Tool (SWAT).

Pour évaluer l'applicabilité de SWAT au contexte du BCP, le modèle a été calibré et validé en employant les données de l'écoulement d'eau et du rendement de sédiment au cours d'une période de trois années (2004 - 2006) dans le sous-bassin de la rivière Caño Quebrado, dont la superficie est de 75 km^2 avec un secteur des fermes d'ananas éclosantes et de pâturage de bétail. Le modèle a montré une performance exceptionnelle pour la moyenne hebdomadaire de l'écoulement d'eau et de base simulé (tous les coefficients de Nash Sutcliffe > 0.76, sauf la période de validation de l'écoulement de base), a produit peu d'erreur significative, et a décelé des prédictions fortement précises de rendement cumulatif annuel d'eau. Bien que le SWAT soit capable de simuler des rendements du sédiment cumulatif sur une précision acceptable, le modèle prédisait médiocrement le rendement moyen mensuel de sédiment (le coefficient de Nash Sutcliffe pour la période de la calibration = 0.48). Selon, l'analyse de sensitivité qualitative et quantitative laquelle constate que cette impression était probablement suite aux effets composés de l'imprécision des divers paramètres de 'input' (comme ceux du Modified Universal Soil Loss Equation, MUSLE, pour la modulation de la culture d'ananas et des pâturages), des incertitudes de données appliquées (comme la résolution et la fiabilité de données du sol), et finalement l'incapacité de SWAT de moduler la couverture d'ananas. En général, cette étude illustre que SWAT pourrait potentiellement être un support avantageux pour l'utilisation dans le BCP, cependant les questions de pénurie de données devront être résolues, incluant les cartes de sol, la représentativité spatiale et temporelle des données de champ d'écoulement de l'eau et de sédiment, et les estimations précises pour les paramètres d'MUSLE. Les modifications à la structure de modèle augmenteraient aussi l'exactitude de prédiction, spécifiquement les composantes de la modulation de l'eau souterraine et de la croissance de plante.

Resumen

La Cuenca Hidrológica del Canal de Panamá (CHCP) proporciona agua para manejar el Canal, generar la hidroelectricidad, y suministrar provisiones de agua a las poblaciones locales y metropolitanas. Con un presupuesto de agua prensada, cuya consecuencia en la región es la poca posibilidad de adaptarse a los efectos potenciales de los cambios del uso de tierra insostenibles o a los efectos de los cambios climáticos, los cuales por consiguiente amenazan cambiar el cronometraje y los flujos de agua. Además, la capacidad de almacenaje de los reservorios de canal necesaria para el uso del agua durante la época seca, esta comprometida por la sedimentación producida principalmente por la erosión y los derrumbes los cuales son causados por el insostenible manejo de los terrenos de la Cuenca. Considerando este contexto, se exigen útiles para mejorar la conservación y la planificación del uso sostenible de los recursos naturales, las actividades del manejo de la cuenca, y por ultimo pronosticar los riesgos. El Soil and Water Assessement Tool (SWAT) es un modelo de simulación, instrumento ideal para apoyar tales iniciativas en la CHCP.

Para evaluar la aplicabilidad del dicho modelo para su uso en el contexto de la CHCP, el SWAT fue calibrado y validado para el flujo de agua y la producción de sedimento durante un período de tres años (2004 - 2006) en la microcuena del Río Caño Quebrado, cuyo área es de 75km^2 con un sector floreciente del cultivo de piña y una fuerte tendencia de cría de ganado. El modelo mostró una actuación excepcional para el promedio simulado del flujo del agua y flujo base semanales (todos los coeficientes de Nash Sutcliffe > 0.76, salvo el período de validación del flujo base), generó poco error significativo, y demostró las predicciones sumamente exactas de la producción anual acumulativa de agua. Aunque el SWAT fuera capaz de simular el rendimiento de sedimento acumulativo con una precisión aceptable, el modelo predecía el rendimiento de sedimento mensual promedio con poca exactitud (calibración Nash Sutcliffe coeficiente = 0.48). Un análisis de sensibilidad cualitativo y cuantitativo revela que esto era probablemente engendrado por los efectos compuestos de varios parámetros de ‘input’ (tal como aquellos de la Modified Universal Soil Loss Equation (MUSLE) para la modulación del cultivo de piña y de la cobertura de pasto), incertidumbres de los datos aplicados (tal como la resolución y fiabilidad de datos de suelo), y la incapacidad de SWAT de modelar la cobertura de la planta de piña. En general, este estudio ilustra que SWAT podría ser un instrumento de apoyo fructuoso para su uso en la CHCP; sin embargo, las cuestiones de escasez de datos tendrán que ser resueltas para que su aplicación sea eficaz– incluyendo aquellas de los mapas de suelo, la representatividad espacial y temporal de los datos de campo del flujo de agua y del sedimento suspendido, y estimaciones precisas para los parámetros de MUSLE. Las modificaciones de la estructura del modelo mejorarían la exactitud de predicción, específicamente los componentes de la modulación de las aguas subterráneas y del crecimiento de planta.

Acknowledgements

Dr. Robert Bonnell, Dr. Catherine Potvin and Dr. Andrew Hendry, thank you for your support and guidance.

I am grateful for the financial support provided to me by the NEO program, the Levinson family, NSERC funding from Dr. Robert Bonnell and the Instituto de Investigaciones Agropecuarias de Panamá.

Dr. Robert Quiroz and his team at the Centro International de la Papa, especially Percy and Heline, for their assistance and friendship.

Dr. Duane Bartholemew for his friendship and support.

The Smithsonian Tropical Research Institute for allowing me to use their faculties and equipment.

To the staff at the Instituto de Investigaciones Agropecuarias de Panamá, thank you for hosting a young, naïve Canadian and inviting her to be a member of your institution. In particular, I thank Miguel Saramiento, Ruth del Sid, Rubiela Garcia, and Manuel de Gracia for sharing the success and tribulation, the excitement and the disappointment, the trips, the cultural exchanges as well as the culture shocks, the learning, and your friendship with me during my sojourn in Panama.

I am especially thankful to my friends and family who have encouraged me to pursue this path, even in the face of significant obstacles and adversity. Kathryn Clark, I am forever indebted to you for the support and love you provided me with in the hardest of times.

Cusiccoyllor, without you I could not have arranged the pieces.

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List of Acronyms and Abbreviations

ACP	Autoridad del Canal de Panamá (Panama Canal Authority)
AED	Academy for Educational Development
CCA	Cerro Cama weather station
CHR	El Chorro weather station
CICH	Comisión Interinstitucional de la Cuenca Hidrográfica (Interinstitutional Commission of the Panama Canal Watershed)
CQ	Caño Quebrado River basin
CN	Curve Number of the Soil Conservation Society (SCS)
DEM	Digital Elevation Model
ENSO	El Niño Southern Oscillation
ES	Ecosystem Services
HRU	Hydrological Response Unit
IDIAP	Instituto de Investigaciones Agropecuarias de Panamá
I&N	Intercarib S.A and Nathan and Associates
MUSLE	Modified Universal Soil Loss Equation
NGO	Nongovernmental Organizations
NRSC	Natural Resources Conservation Services
PCW	Panama Canal Watershed
PES	Payment for Ecosystem Services
PMCC	Programa Monitoreo de la Cuenca del Canal (PCW Monitoring Project)
PTFs	Pedotransfer Functions
RUSLE	Revised Universal Soil Loss Equation
STRI	Smithsonian Tropical Research Institute
SWAT	Soil and Water Assessment Tool
TCH	Tinajones, Caño Quebrado, and Los Hules River basins
USDA	United States Department of Agriculture
USLE	Universal Soil Loss Equation
ZAN	Zangangua climate station

1.0 Context

1.1 The Panama Canal Watershed

The Panama Canal Watershed (PCW) (Map 1, page 9) provides the billions of cubic meters of fresh water necessary to transit ships through the Canal each year, an activity upon which the national and international economies depend. Of the water supplied by the watershed, Canal operations are the principal consumer, using between 59 - 64% of total annual water yield (ACP, 2006a, Ibáñez et al., 2002). The local effects of a growing population and increasing affluence in the metropolitan region of the PCW are raising energy demands (hydroelectrically generated) and potable water consumption. Together, these activities use up to 30 - 34% of the annual water yield (ACP, 2006a, Ibáñez et al., 2002). While agricultural activities, principally livestock grazing and small non-commercial crops, use minimal amounts of water (6 - 7%) (ACP, 2006a, Ibáñez et al., 2002), they contribute to ecosystem degradation, principally through the associated effects of soil erosion and compaction. Together, these three points of consumption exploit nearly the entire annual water yield; as such, there is little opportunity to accommodate additional and growing water demands. This, coupled with the impending effects of climate change, threatens the consistency and quantities of water supplies and flows from the watershed. In fact, some of these effects have already manifested themselves, resulting in reductions in precipitation and temperature increases, with particularly strong deviations from average years during El Niño events (e.g. 1982/1997). During these events, drought forced reductions of shipping drafts, citizen water and energy shortages, and severe ramifications for the national and agrarian economies (Vargas et al., 2000).

It is paradoxal, then, that this tropical watershed with an abundance of fresh water (average annual precipitation ~ 3000mm) is facing water scarcity issues. Dealing with these realities means circumspectly planning and implementing watershed management plans and conservation activities. Managing the demand side of water consumption, especially when working within the realm of international trade, is on the whole impractical. Accordingly, Panamanian public and private institutions aim to manage the supply side. In the 1970's, as awareness and apprehension of the unfavourable effects of deforestation grew, the Panama Canal Commission (the US-led Canal authority) created parks to protect the upper reaches of the PCW - where cloud forests supply 70% of annual flow into the Canal (Nichols et al., 2005) - and riparian zones to control erosion. The most conspicuous attempt to accommodate rising demands, however, is the current undertaking of the expansion of the Canal.

Despite these efforts to conserve water flows and abate erosion, the Autoridad del Canal de Panama (ACP) must spend millions of dollars annually to dredge sediment deposited in the benthos of the reservoirs to maintain reservoir depth and adequate water supplies for ship transit during the dry season deficit. The Programa Monitoreo de la Cuenca del Canal (PMCC) (1999) speculates that sedimentation of the reservoirs is largely due to mineral sediments, primarily from landslides during heavy rainfall events, and to a lesser extent, organic sediment caused by the lake's biological productivity (PMCC, 1999), (Ibáñez et al., 2002). The threat posed by grazing and agricultural practices, when unsustainably implemented, has a twofold repercussion for the PCW. While these activities do render areas of the watershed more susceptible to landslides and erosion (Loewenberg, 1999) they may also compact soils, thereby increasing runoff rates and reducing infiltration and aquifer recharge. Such changes to soil structure can result in water flow timing shifts and dry season baseflow reductions – important factors upon which the Canal depends for operations during the water deficit months.

Socio-ecological and conservation activities undertaken in the PCW involve the participation of many organizations with a diverse set of mandates. Of principal importance is the ACP, administrators of the Canal and its operations, which presides over the Comisión Interinstitucional de la Cuenca Hidrográfica (CICH). CICH is a syndicate of 8 member organizations that attempts to function as an integrated watershed managing body in the PCW (CICH, 2000). This commission, however, has been criticized because of its centrality and its exclusion of other important bodies working within the PCW (GreenCOM, 2002). MIDA (Ministerio de Desarrollo Agropecuario) and ANAM (Autoridad Nacional del Ambiente), two of the government CICH members, are of paramount importance for sustainable agricultural, environmental monitoring, and outreach throughout Panama. The Instituto de Investiagciones Agropecuarias de Panamá (IDIAP) is involved in agricultural research and extension work in Panama, working closely with ANAM, MIDA and Panamanian populations. AED (Academy for Educational Development), an important nongovernmental organization (NGO) in the area, contributes to all aspects of sustainable development goals, partaking in environmental monitoring and sustainable agriculture projects. Currently, with a subvention of over $3.0 million dollars, some of these organizations are working together to implement sustainable watershed management pilot projects in the Tinajones, Caño Quebrado, and Los Hules Rivers basins (TCH), to generate favourable outcomes for the local populations and Canal stakeholders.

Monitoring and managing an area as diverse as the PCW – where the physical landscape (ecology, geology, geography, land-use/land-cover, etc.) and the social landscape (culture, political and economic status, assess to technology, etc.) are spatially and temporally variable – requires a set of integrated tools, institutions, and frameworks. Beyond the institutional reforms already made (e.g. the formation of CICH, decentralization, collaborations), complementary geo-spatial tools that allow for visualization, modeling, and consolidation of such information can be of invaluable importance for the long-term sustainability of the watershed and the Canal. While an extensive Geographic Information Systems (GIS) database has and is still being developed for the region, management planning could also benefit from a watershed-scale model that is able to meet the generalized needs of the PCW to suggest best management practices, develop conservation plans, predict and prepare for possible outcomes of climate change etc.

Recently, a new class of conservation paradigms, Payment for Ecosystem Services (PES) (see section 3.5), has been proposed as a mechanism to protect the PCW, potentially reduce poverty, and conserve or improve the ecosystem. A pilot project to examine the socioeconomic and environmental feasibility of PES has commenced in TCH, spearheaded by researchers from IDIAP under the auspice of the Food and Agriculture Organization (FAO). An ideal PES program in the PCW would involve reallocation funds spent on watershed management and protection, dredging, and/or potable water production and distribution to remunerate land-users (agriculturalists and/or pastoralists) for converting to more sustainable land-use/land-covers. Theoretically, such changes should significantly reduce erosion production and potentially help ensure more consistent water supplies. The success of which, however, will depend heavily on its planning and implementation. The exact PES mechanism(s) (e.g. payment amount and scheme, services considered, services buyers and sellers, etc.) to be employed depends on the results of the ongoing research to identify, valuate, and quantify ecosystem services in TCH and other pilot project basins in the PCW.

1.2 The Pilot Study Area: The Tinajones, Caño Quebrado, and Los Hules River Basins

TCH basins are located in the central region of the PCW, representing about 4.5% of the greater watershed area. The largest of the three river basins is Caño Quebrado (CQ), with a total catchment area of 74 km^2. Together, the Tinajones and Los Hules River basins, which join prior to the main catchment outlet into Lake Gatun, are nearly equivalent to CQ in size (~80 km^2) (Map 1, page 9).

Although land-use in the PCW is generally not considered to be in transition, – most titled land is used for livestock grazing and remaining forests are protected (PMCC, 1999) – the TCH area has caught the attention of watershed monitors due to an unexpected and notable land conversion trend. Since 2001, pineapple plantations have been rapidly cropping up – generally converted from pastures – turning the TCH area into a 'hotspot' for pineapple culture (Figure 1). In fact, in the last eight years the area planted to pineapple has roughly tripled and it is projected to continue to grow at similar rates (Martez and Vergara, April 2004). The increasing land area under pineapple cultivation has left many wondering what long-term impacts of this expansion could have in terms of sediment generation and water flows.

Currently, pasture for cattle ranching is the principle land-cover in TCH (74%) followed by pineapple cultivation, currently claiming 14% of the land area (Map 2a, page 10). There are a total of 27 towns and hamlets in the area with a population of about 4100 (Marín and Yee, 2004). Sixty-six percent of the population works in the agricultural sector (Marín and Yee, 2004), many of whom work on pineapple plantations or in one of the three nearby pineapple packing plants. As in the rest of Panama, there exists a large inequality in land tenure (Contraloría, 2006); in fact, several of the plantation barons reside outside of the area, either in the nearby capital or other large urban centers (Map 1, page 9). Due to the growing number of pineapple plantations and the increased need for labor, many workers have been contracted from other remote provinces, earning an average pay of about 3-4 US$ per day (IDIAP, 2007).

Soils in the area are principally fine clays or clay-loams of the Ultisol soil class and the Udult suborder (IDIAP, 1996, USDA and NSCR, 2005) – equivalent to the Humic Acrisols of the FAO soil classification system (FAO and UNESCO, 2003). Although, in general, high clay content soils are not particularly susceptible to erosion, soils of the area are thought to be of kaolinitic clay origin with clayey B horizons (FAO and UNESCO, 2003, Godsey et al., 2004) which are known to be structurally unstable, prone to crusting, – this has been observed in TCH during the dry season – and are easily compacted by cultivation (Lal, 1990).

The climate is characteristic of the sub-humid tropics, with an average annual rainfall of 1887 mm (AED, 2004a) and two distinct seasons: the wet season – May to December – and the dry season – January to April. The most intense storms are in October, while monthly average precipitation in February and March commonly approaches zero. This intense seasonality means extreme dry seasons that can cause cracking on degraded soils and lead to high surface runoff rates and heavy storms in the wet season that can expose soils with no vegetative cover to rainfall impact. While some protection can be afforded by choosing appropriate crops and planting patterns, farmers in the TCH area do not tend to use such strategies (Figure 1). Average annual temperatures are 26ºC, however, diurnal temperatures range from 23ºC to 33ºC; temperatures do not greatly fluctuate seasonally. Seventy five percent of the area is less than 100 meters above sea level, although some of the highest points surpass 200 meters (Map 2b, page 10).

a)  b) 

Figure 1a & 1b: Pineapple plantations in the TCH basins. July 2006.

It is for the above-mentioned reasons that the effects of the expansion of pineapple farms on sediment and water flow and quality in the TCH basins have been under enquiry by the ACP and other agencies since the expansion began. While a lack of historical data renders an analysis unfeasible, the general assumption has been that sediment yield in the TCH basins is on the rise due to the pineapple production expansion.

1.3 Pineapple cultivation and management practices in TCH River Basins

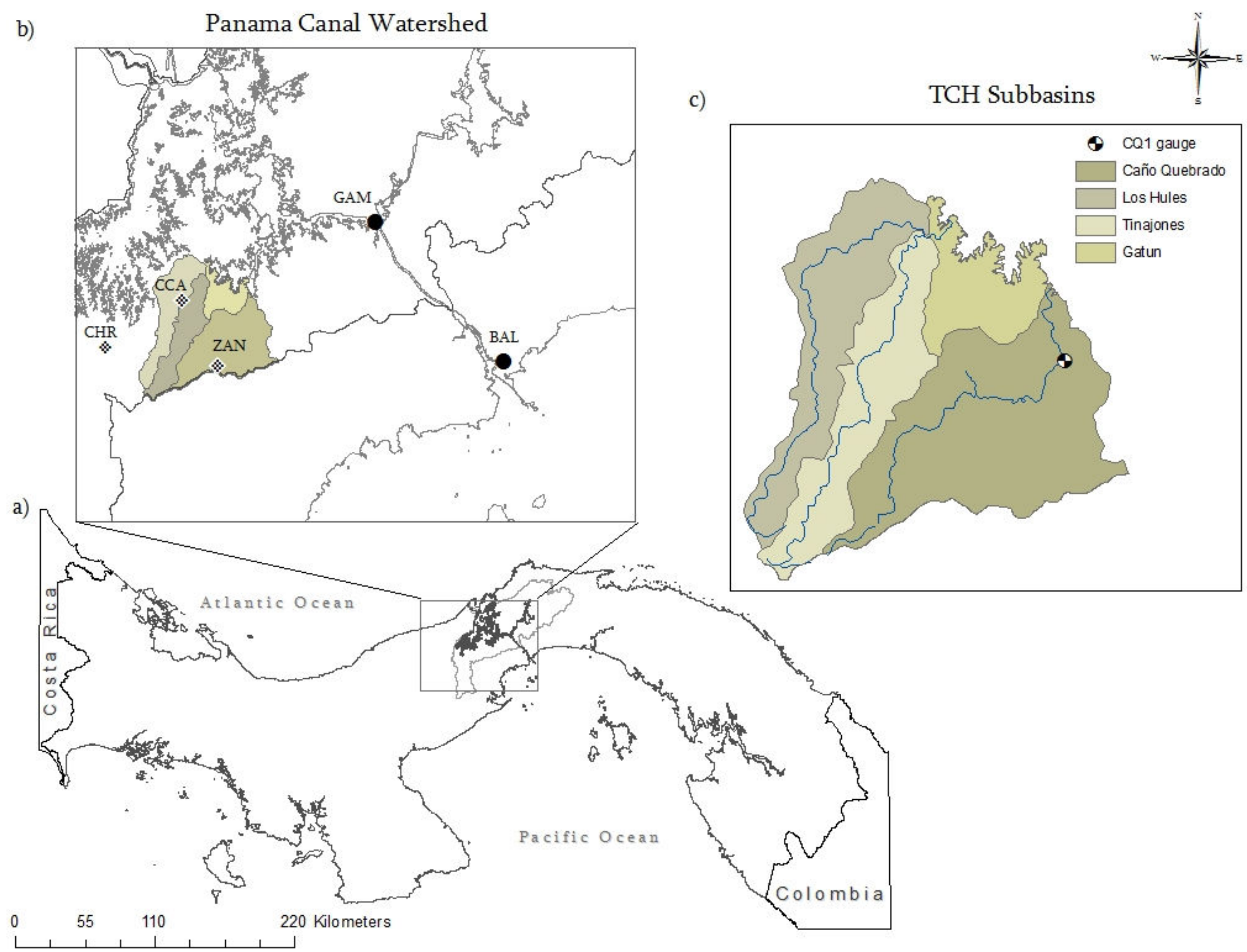
Pineapple production in the TCH basins is intense and farmers do not generally employ soil conservation (erosion prevention) techniques (Martez and Vergara, 2004). Straight up and down cropping patterns, such as those shown in Figure 1, are commonly observed in the region. In 2004, Martez and Vergara (2004) documented erosion on all pineapple farms in TCH, classifying 33% of farmland as severely eroded. According to their survey, all pineapple farmers (with the exception of one) identified erosion and its severity as an important issue. Considering soils in the area are susceptible to degradation and that the landscape topography of the area is largely of undulating slopes (average slope 8%, maximum 49%) (Figure 1), reducing erosion in the area will largely hinge on crop cover, cropping patterns and planting in appropriate areas and at appropriate times.

The unsustainable management of pineapple farms in the TCH is conceivably due to a lack of information on sustainable farming practices or because such practices (preparing land for planting along contour lines or on terraces) are labor intensive and require capital, time and accessibility to tools and other resources. Although a majority of pineapple farms in the area are large-scale commercial plantations (Martez and Vergara, 2004) that may have such resources, there are also a number of small-scale pineapple farmers in the area that may lack similar access. An additional issue of paramount importance is the fact that farmers have no external incentive to adhere to the regulations outlined in the best management practices guide for pineapple farming in Panama (OIRSA, 1999).

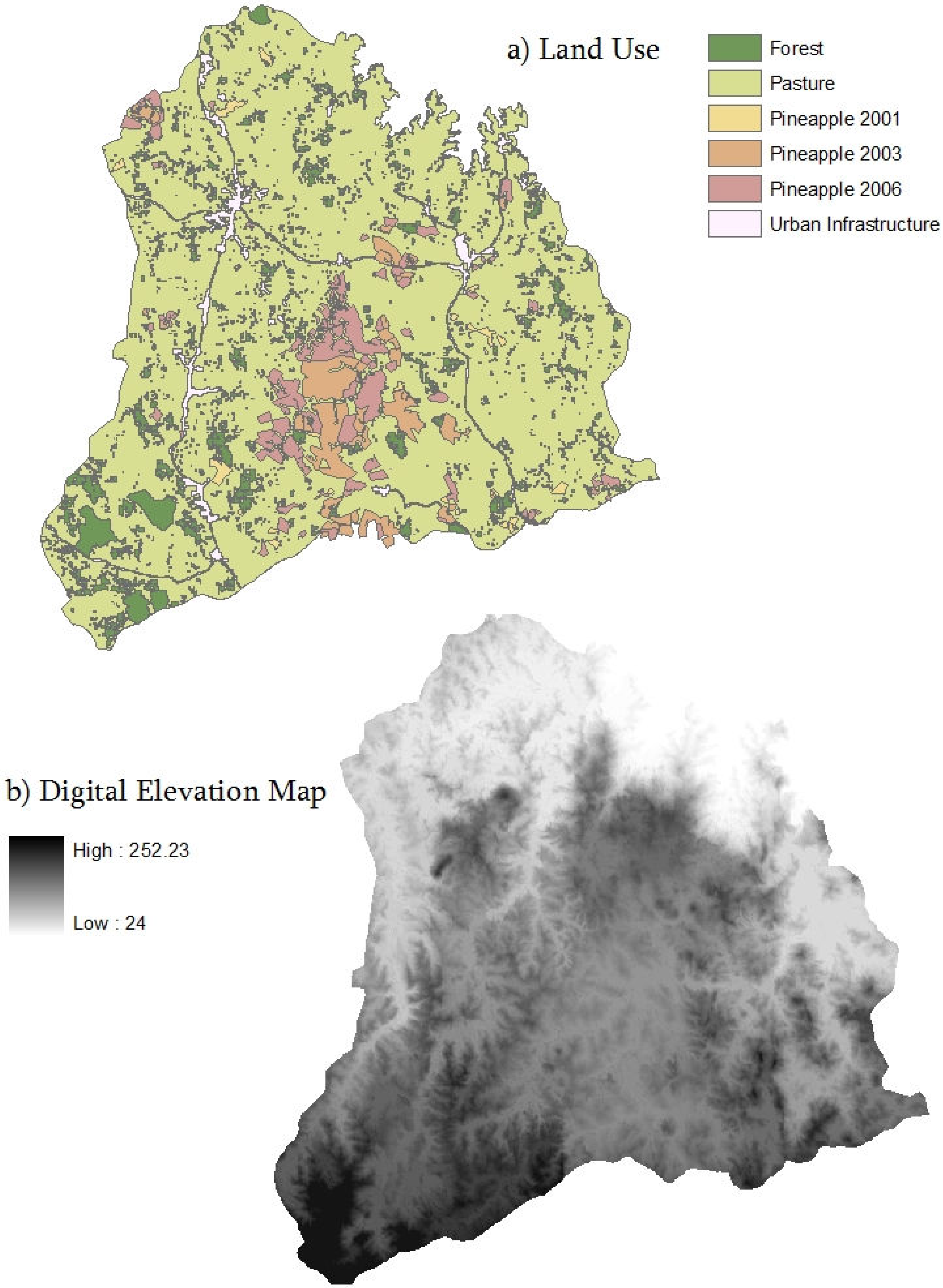
1.4 Representativeness of the pilot study area

Although elected as the pilot study area in 2000 by CICH and other agencies, the TCH does not adequately represent the greater PCW. Achieving the objectives stated in the following section (Section 2) and discussing the results of this study will require a brief reference to certain key differences. The area is not sufficient in size to represent the rainfall variation exhibited across the watershed (known as the isthmian rainfall gradient). In fact, rainfall in TCH more closely resembles precipitation patterns along the Pacific coast (average 1700mm) than the Atlantic side (average 3000mm) (Map 1, page 9). In general terms, however, the subbasins receive about 550mm less annual average rainfall than the greater watershed. The underlying geological landscape and soils of the PCW also varies greatly. The Caño Quebrado and Tinajones River basins are representative of about 8% of the formations of the greater watershed (MICI, 1991), however, the geology and soils of the Los Hules River basin is distinct from other areas (MICI, 1991). Bearing these two factors in mind, there exists a great variation of natural vegetation and geographical formations across the PCW. Within a small radius around the tri-basin area, land-use is relatively analogous, however, comparisons beyond this range break down when up-scaling to the PCW. While land-use in most of the greater watershed parallels that of the TCH area (about 43% of the total area is pasture cover mostly concentrated along the metropolitan corridor), the eastern and western upper reaches of the PCW (Map

1, page 9) are dense moist tropical and cloud forest cover. Given this, the pilot study area will only be indicative of certain areas (pasture, agriculture, and urban infrastructure) of the greater watershed.



Map 1: a) The republic of Panama. The Panama Canal Watershed (PCW) is demarcated in grey; b) Location of the Tinajones, Caño Quebrado, and Los Hules River basins (TCH) within the PCW. Data taken from the Balboa (BAL) and Gamboa (GAM) weather stations and the rain gauges Zanguenga (ZAN), Cerro Cama (CCA), and El Chorro (CHR) were used as SWAT input; c) the TCH subbasins and their primary rivers. The Caño Quebrado gauge used for model calibration is indicated.



Map 2: a) Land-use in the TCH basins. There are minimal amounts of fragmented forest, which primarily consist of forest plantations (7% of total land area) or small strips or patches used for property separation or along riparian zones (2% of total land area). Urban infrastructure, chiefly paved roads, houses, poultry (4 in total) or swine (2) farms, is minimal (2% of total land area), and a near negligible amount of land is in subsistence agricultural production; b) digital elevation map of the TCH basins.

2.0 Objectives

The economic costs of increased reservoir sedimentation and shifts in water yields and flow timings are potentially high, so identifying the causes of unsustainable practices and ensuring reductions in erosion-causing activities within the PCW are main objectives of the ACP and other political bodies. Developing PES programs and watershed management and conservation strategies in the PCW would largely benefit from having a reliable tool to predict the effects of different land-uses on erosion and water yields, the results of which could be combined with other analyses (i.e. social, economic, climate change models, etc.). This would allow watershed managers to identify appropriate conservation methods for the region (agroforestry, silvopastoral systems, sustainable cropping patterns, etc.) that are effective at controlling/reducing erosion or allow erosion 'hotspots' to be pinpointed and identify unsustainably managed areas contributing most to reservoir sedimentation. The research undertaken in this thesis takes a first step to achieving these goals.

The objective of this study is to calibrate and validate streamflow and sediment yield in the TCH using the Soil and Water Assessment Tool (SWAT), a distributed hydrological model. Due to limited data availability only one of the three subbasins is modeled (Caño Quebrado). Notwithstanding this limitation, many studies conducted in the TCH area have been assessed at the tri-basin scale. As such, much of the content of this paper is discussed in light of the three basins to draw conclusions for SWAT model use in TCH and up-scaling to the greater PCW. The results of this study will open the door for a theoretical discussion of SWAT's ability to model other land covers, such as forests, and to assess the usefulness of this model in the context of watershed management in the PWC and the implementation of a PES program. Although many case studies and applications of SWAT have been published to date, this study contributes to the literature by applying SWAT to a tropical watershed with a large pineapple cultivation component, something as yet not done.

3.0 Literature Review

Simulations using complex modeling programs, such as SWAT, require a fundamental comprehension of the underlying processes that govern water and sediment movement in the catchment under study. This review discusses some of the key features of hydrology and erosion processes with specific regard to ecosystems of the humid tropics and the SWAT model and its applications. This is followed by a brief review of pineapple production and payments for ecosystem services.

The tropics may be defined as the area between 23^{o} north and south of the equator, and is further categorized as arid, semi-arid, humid, and sub-humid depending on wet season duration; regions of Panama may be classified as humid and sub-humid. In recognizing these distinctions, the following discussion will refer to the tropics in general, but focus on the humid and sub-humid regions.

3.1 Hydrology in the Tropics

Some of the key factors that influence flow regimes in humid tropical climates are highlighted below; it should be acknowledged, however, that there are other factors that are not discussed (i.e. topography, geology, etc.), that also affect system hydrology. The bulk of literature and research on tropical hydrology has focused on the role of tropical forest ecosystems and its conversion to the human modified, agroecosystem. Therefore, in describing the processes and factors which determine water flow pathways, a comparison with the ecosystem it once was (forested) is expected.

Climate Patterns and the Water Balance

Precipitation patterns play an important role in the runoff production process in a catchment, in particular the intensity, frequency, and duration of storms. In the humid and sub-humid tropics, high amounts of intense precipitation and seasonality are key climatic characteristics. During the dry season, precipitation is infrequent and generally does not last long. In such cases, water enters the shallow soil layer and evapotranspires or percolates through the soil, generating little or no surface water runoff. Dry season streamflow, therefore, is largely baseflow contributions from latent soil-water storage and groundwater reserves. Conversely, during the wet season, when most of the annual precipitation falls, storms are generally intense, more frequent, and last longer. Overland flow is favoured during such storms, as soil infiltration capacity may be rapidly exceeded and, if infiltration permits, groundwater reserves may be replenished after dry season release.

Canal operations are highly dependent on the amount of precipitation and the timing of resultant streamflow received in the PCW. Ship transiting, which uses millions of gallons of freshwater daily, may only continue during the dry season water deficit if sufficient supplies are collected during the wet season and are stored in Canal reservoirs. Currently, such an excess of inflow is received during the wet season that reservoirs must be spilled into the ocean in order to avoid flooding; yet extreme dry seasons, such as those produced by El Niño Southern Oscillation (ENSO) events, have resulted in severe water shortages (ACP, 2006a).

In the 1980s, a decreasing precipitation trend over the PCW was observed, leading researchers to conclude that this would result in decreased runoff that could severely affect Canal operations (Rand and Rand, 1982). These claims are in agreement with other studies which maintain that annual rainfall has been declining in the Caribbean over the last few decades (Peterson et al., 2002). The ACP challenges these results, affirming that there is no significant decrease in overall precipitation in the area, nor are there overall reductions in average annual runoff (ACP, 2006c). The ACP does, however, show that average monthly temperatures are on the rise and that the events produced by ENSO do in fact reduce precipitation and runoff in the PCW by a factor of 20 - 30%, principally during the wet season. Although climate patterns across the Panamanian isthmus are dictated by sea surface temperature and related ENSO events (Graham et al., 2006, Enfield and Alfaro, 1999), observed temperature shifts may also be attributed to global warming (Graham, 1995). Rising temperature, among other effects of global warming, could alter certain aspects of the hydrological cycle; for example, provoking increased evapotranspiration and reductions in streamflow.

Soil Hydraulic Properties

Soil hydraulic properties, such as the saturated hydraulic conductivity (K_{sat}), have been recognized as a major control point for determining water flow pathways in the tropics (Elsenbeer et al., 1999, Bonell, 2005, Bonell et al., 1981). Elsenbeer (2001) suggests that overland flow is the favoured flow path of Acrisol soils, allegedly due to the pronounced reduction in the magnitude K_{sat} with increasing depth and the predominance of kaolinitic clays at the B horizon (Elsenbeer, 2001). Accordingly, these soil characteristics may, if surface characteristics so permit, encourage rapid overland flow and potentially increase soil erosion vulnerability. Elsenbeer and Lack (1996) also observed that Acrisols frequently drain via soil-pipe networks (Elsenbeer and Lack, 1996). On Barro Colorado Island, where soils have also been classified as Acrisols, soil-pipe networks are estimated to be on the order of one pipe per square meter (Kinner and Stallard, 2004).

Human land-cover choices and land (mis)management practices, which compromise porosity and reduce vegetative cover, may alter inherent soil hydraulic properties and preferred flow pathways. For example, intensive grazing or mechanical soil disturbances (by plows or other vehicles) can compact the soil profile, reduce the infiltration capacity, and increase surface water runoff (Giertz et al., 2005, Mwendera and Saleem, 1997). With this in mind, the aforementioned pipe-flow observed in Acrisols may only be a significant drainage process in undisturbed, forested catchments (where these networks have been documented). Disturbances from agriculture may inhibit the formation and maintenance of such drainage networks and in turn promote overland flow pathways.

Land-use/Land-cover Change

In a study to model the effects of land-use change on annual streamflow using the Hydrological Land-use Change (HYLUC) Model, the Center for Land-use and Water

Resources Research predicted that conversion of all remaining forested land to pasture cover in the PCW would increase cumulative annual streamflow by 18 - 29%, depending on the catchment (Calder et al., 2001). The increased streamflow has been attributed to the lower infiltration and soil-water retention characteristics typically exhibited by crops or pasture when compared with tropical forest ecosystems; in fact, such observation have been well documented in deforested tropical catchments *in situ* (Bonell, 2005, Bruijnzeel, 2004). Significantly lower evapotranspiration rates of most agricultural crops when compared to tropical forests may also contribute to streamflow increases (Bonell, 2005, Bruijnzeel, 2004).

Bruijnzeel (2004) asserts that conversion of forest to agricultural land provokes increased wet season and surface runoff flow and strong declines in dry season baseflow, particularly if surface disturbances reduce infiltration capacity (Bruijnzeel, 2004). According to the existing literature, groundwater and lateral flows, rather than surface runoff, are presumed to be the dominant water movement processes in tropical forests (Bruijnzeel, 2004). Tropical forests have been shown to retain water during the wet season, which is then slowly and steadily released as baseflow during the dry season (Bruijnzeel, 2004). On the other hand, crop or pasture cover, which commonly have shallower rooting depths and less root matting, are assumed to favour surface runoff processes, rather than retention and infiltration, in the wet season and therefore do not display the slow baseflow release during the dry season. These differences in flow preferences of agricultural and forested catchments has been demonstrated in the PCW by Intercarib S.A and Nathan and Associates (I&N) (1996) and PMCC (1999). In a paired catchment study comparing streamflow patterns of an agricultural catchment of principally pasture cover and a forested catchment, both groups illustrate that the agricultural catchment provides a lower proportion of stream flow during the dry season and that groundwater reserves are slower to recharge during the wet season when compared with the forested catchment (I&N, 1996, PMCC, 1999).

3.2 Soil Erosion in the Tropics

The soil erosion process is intrinsically related to many of the same factors that determine flow pathways in a catchment and they may be similarly affected by human landscape alterations. Lal (1990) divides factors driving erosion into active and passive forces. Passive forces are climate, soil properties, hydrological characteristics and landforms (Lal, 1990). The principle active force causing erosion is the land-cover/land-use choices made by humans, which will be the focus of the following discussion.

Accelerated Erosion

Natural, geological erosion may be accelerated by human activities which alter natural vegetative cover; a significant and growing issue in tropical regions (Lal, 2001). According to Oldeman (1991) the direct factors driving accelerated soil erosion are deforestation, overgrazing, improper agricultural practices, and over-exploitation of vegetation[1] (Oldeman et al., 1991). Such activities may cause erosion rates to exceed natural soil regeneration rates, triggering topsoil loss and nutrient abatement, consequently depleting soil productivity and resulting in soil degradation – deterioration of the physical, chemical and biological properties of the soil (Lal, 2001).

Land-use/Land-cover

Land conversion, which considerably disturbs the soil surface and protective vegetation, often results in high amounts of sediment yields in tropical catchments. Based on empirical evidence, Lowenberg (1999) indicates that landslides are the principle source of sedimentation in the PCW, owing to land conversion of forested land to pasture in the mountainous regions of the eastern PCW. Landslides, the mass movement of sediment, are a natural part of the erosion process but may also be human induced. Steep lands or

[1] These drivers of soil erosion do not include the indirect forces which may drive land degradation, such as socioeconomic, cultural, or political factors.

riparian zones where vegetative cover, which helps maintain soil structure, has been removed or modified are particularly susceptible to landslides, chiefly during intense wet season storms. Other researchers, however, maintain that the principle cause of landslides in the PCW is not dictated by land conversion, but rather the variable climatic characteristics of the watershed. According to Stallard and Kinner (2002), landslides occur when intense precipitation causes surface runoff amount and velocity to exceed a runoff threshold limit after which landslides occur, valid for both forested and agricultural catchments (Stallard and Kinner, 2005). In fact, as recognized by Ibañez et al. (2002), both suppositions are likely correct in that land conversion to pasture can increase surface runoff and, therefore, would require less precipitation to reach the runoff threshold limit, consequently increasing landslide susceptibility.

Beyond land conversion, land management practices which disturb soil surfaces, such as agricultural activities, grazing practices, or construction, play a noteworthy role in exacerbating erosion. In agricultural fields, dirt roads and tracks can significantly contribute to sediment yield, up to 35% of the total yield as observed by Dunne (1979) (Dunne, 1979). Such observations are likely due to mechanical disturbances from vehicles and plows that disturb the soil surface and promote erosion through reduced infiltration and increased surface runoff. Similarly, livestock overgrazing can promote erosion through the removal of protective vegetative (pasture) cover or via livestock trampling which compacts soils and exposes them to water erosive forces. This can be further exacerbated by increases in slope steepness (Mwendera and Saleem, 1997). Other activities, such as urbanization, road building, or mining activities, have been shown to produce sediment yields equal to or in excess of those observed upon forest clearing (Bruijnzeel, 2004). However, sediment yields from certain land-cover/land-uses and/or their changes can vary considerably with soil type and the local geologic characteristics (Bruijnzeel, 2004).

Conversely, choosing appropriate land-cover and management practices in agricultural fields can curtail erosion. Several methods may be applied to agricultural landscapes, such as mulching or cover crops, contour cropping, terraces, agroforestry systems, among others, which can effectively reduce erosion by minimizing raindrop impact and/or retard surface runoff velocity (Lal, 1990). Conservation tillage or no-till practices can also reduce the impacts of mechanical disturbances. These measures may enhance soil infiltration and improve soil structure. (See section 3.4 for details on these methods and their applications).

The promotion of land-use/land-cover modifications, such as reforestation, to prevent erosion has been a high priority in the PCW. This is because sedimentation of Canal reservoirs, which decreases the reservoir storage capacity, is a direct threat to Canal operations, predominantly during the dry season. Major reforestation programs, encouraged by government funded monetary incentives to reforest, were successfully initiated in the late 1990s (FAO, 2002). The program did not restrict the type of species to be used for reforestation (native or exotic trees), nor were any stipulations made on management practices [2]; therefore, reforestation of the PCW has been largely of monoculture teak (*Tectona grandis*) plantations. The program effects, which were intended to reduce erosion on hillslopes and in riparian zones while simultaneously securing water supplies, have not, in all likeliness, been realized. The natural underbrush in forests, which can protect soils from erosive forces, is often wholly removed in the teak plantations of the PCW in order to reduce resource competition. Furthermore, although still a controversial conjecture, reforestation may reduce inflow into the Canal (Calder et al., 2001).

With similar objectives, silvopastroal systems are being heavily promoted in the PCW, aided by the distribution of koronivia grass or 'pasto mejorado', *Brachiaria humidicola*, a drought resistant grass endemic to tropical Africa that grows well in shade and under medium to heavy grazing intensities (FAO, 2007). Silvopastoral systems may be an effective measure for erosion prevention, considering approximately 35% of the PCW is currently in pasture cover used for grazing; most of which is concentrated in the populated, lowlands of the watershed (ANAM & ACP, 2006). Although no studies have

[2] The only exemption is a mandatory increase in the minimum number of years for teak crop rotation, from 20 to 25 years.

been published to date, grazing practices may indeed be a significant source of erosion due to the aforementioned effects of livestock, which can be further intensified during the dry season if vegetative cover is compromised due to drought. In fact, overgrazing (generally considered to be more than one cattle head per hectare) is likely a significant and mounting issue in Panama considering the number of cattle has more than doubled since 2000 (Contraloría, 2006), while, on the other hand, the amount of land used for grazing is shrinking (Contraloría, 2005). In the TCH basins, more than 50% of pastoralists use practices classified as overgrazing (Martiz and Vergara, 2004).

3.3 Models

Models have been developed to simulate natural processes via a simplified mathematical representation of a natural system. Indeed, such natural systems are more complex and variable than what can be accurately represented in most models (Hann et al., 1995). The following discussion provides a succinct review of some of the current model literature, with specific reference to the SWAT model. This review does not attempt to give an exhaustive list of all hydrological and erosion models and their relative ability at predicting natural processes. For such a resource one may refer to Schmidt (2000), Boardman and Favis-Mortlock (1998) and Refsgaard and Storm (1996).

Models may be classified according to the systematic approach used to describe physical processes. Physically based models rely on physical laws and theoretical principles to describe various model components. This type of model assumes that system responses and relationships are well-understood and can be accurately described via mathematics. Conversely, empirically based models use observations taken from a system in order to characterize it, thereby creating a direct relationship between input and output data. Models may be further classified as deterministic or stochastic. Deterministic models mathematically characterize a system, requiring all data and inputs to be calculated at fixed values. Stochastic models, on the other hand, use statistical methods to predict possible outcomes, allowing modelers to modify input as part of simulation.

Empirical models, such as the Universal Soil Loss Equations [3] (Williams, 1975, Wischmeier and Smith, 1978) and the Soil Conservation Service (SCS) Curve Number (CN) method (SCS, 1972), may be incorporated into physical models. However, the use of such models may be intrinsically problematic, particularly when applied to large-scale studies or in tropical regions. Empirical models are generally developed and validated in non-tropical, small-scale heterogeneous systems and scaling-up of these models to predict processes in larger-systems or tropical settings may not prove reliable. However, the use of Geographic Information Systems (GIS), incorporating Digital Elevation Models (DEM) and land-use/land-cover and soil maps, may facilitate the application of SCS and USLE models at larger-scales (Mitasova et al., 1996, Desmet and Govers, 1996, Stuebe and Johnston, 1990). Furthermore, many empirical models have been derived from experimental data collected in temperate zones; the United States in the case of the USLE and the CN methods. In the tropics, the forces driving natural processes, such as precipitation patterns, temperature, and the response of the ecosystem may be considerably different than in temperate zones (Hamilton and King, 1983). Without modification of these models or the development of new ones suitable for tropical environments, their applications will incorporate some level of unreliability (uncertainty).

Models also range in their ability to simulate across spatial and temporal scales and may be categorized accordingly. Distributed models are capable of predicting response at multiple points within or over an entire catchment. Lumped models focus on simulations in a particular region, such as a hillslope or a single point on a watercourse. Likewise, models may be classified according to the temporal scale modeled. Steady-state models provide snap-shot simulations of single events, while continuous models simulate processes over long time-periods. Distributed, continuous models are extremely demanding with respect to input specifications and require large numbers of high resolution parameters to explain the heterogeneity of a system – variability of topography, vegetation, soils and climate parameters – over large complex spatial scales (Beven, 1985).

[3] This includes the Universal Soil Loss Equation (USLE) as well as the Revised and Modified versions (RUSLE, MUSLE).

Models may be further categorized according to the type and number of processes modeled. Some models examine only a specific process, such as certain components of hydrological response (e.g. groundwater recharge or runoff production), water pollutant loading and transport (which includes sediment, agrochemicals and nutrient movement), crop growth, or weather prediction. Other models, such as SWAT, integrate some or all of these aspects. The ability to simultaneously simulate various processes may be advantageous in certain studies that attempt to examine a system holistically over large temporal and spatial scales, but there may be a trade-off with high input demands.

Choosing the appropriate model depends on the resources, needs and questions asked of the study as well as input data available. For example, predicting instantaneous flood events would require a different model than for the simulation of the long-term impacts of land management practices on water yield. Not only do the spatial and temporal scales differ but also the number of processes to be modeled. Although comprehensive models that model many processes may be able to better describe systems, they require more input data and thus may have more uncertainty associated with them; elaborate and time-consuming calibration and validation procedures are also common in comprehensive models (Hogh-Jensen and Mantoglou, 1992, Refsgaard and Storm, 1996).

The Soil Water Assessment Tool

The Soil Water Assessment Tool (SWAT) (Arnold et al., 1998) is a physically based semi-distributed simulation watershed model that runs on a daily time-step. It relies on climatic, soil property, topographical, vegetative and land management input data and uses both physical and empirical components to predict the impacts of land management practices on water, sediment and agricultural chemical yields in large watersheds over long periods of time.

SWAT was developed by the USDA (United State Department of Agriculture) Agricultural Research Services, as a derivative of the SWRRB (Simulator for Water

Resources in Rural Basins) model (Arnold and Williams, 1995) and the ROTO (Routing Outputs To the Outlet) model (Arnold et al., 1995). Key modeling components were extracted from other watershed-scale models to generate SWAT. The rainfall prediction and hydrology components were adapted from the CREAMS (Chemicals, Runoff, and Erosion from Agricultural Management Systems) model (Knisel, 1982), pesticide transport components were modified from the GLEAMS (Groundwater Loading Effects on Agricultural Management Systems) model (Leonard et al., 1987), and the crop growth component was adapted from the EPIC (Erosion-Productivity Impact Calculator) model (Williams et al., 1984).

Model Processes

SWAT models the runoff and infiltration processes with either the SCS curve number method (SCS, 1972) or the Green-Ampt Mein-Larson method (Green and Ampt, 1911, Mien and Larson, 1973), the latter of which requires sub-daily precipitation data. In a comparison of SWAT model performance using both methods, King et al. (1999) demonstrated that both yielded reliable results for large watersheds when evaluated at the monthly time-step. The authors conclude that there is no apparent advantage or disadvantage for choosing one method over the other (King et al., 1999).

The modified version of the USLE, MUSLE (Wischmeier and Smith, 1978), is used for erosion prediction. Kinnell (2005) argues that the original USLE cannot accurately predict erosion because there is no factor that accounts for runoff-transported sediment (Kinnell, 2005). To improve sediment predictions, the MUSLE equation acknowledges this caveat by replacing the rainfall factor (R_{USLE}) with a runoff factor (R_{MUSLE}), a function of both antecedent moisture condition and rainfall energy. Nearing (2000), however, argues that a high level of accuracy for flow calculations must be achieved in order for this substitution to sufficiently improve model prediction; such accuracy, he affirms, cannot be attained by most conventional methods (Nearing, 2000), such as the CN. Although SWAT does employ an updated version of the USLE, Kinnell (1997, 1994) has shown that the MUSLE is not mathematically sound if R_{USLE} is replaced by

R_{MUSLE} with out appropriate modification of the other equation parameters. This is an important limitation for the accuracy of the SWAT model given that the default values for the K, R, C, and P factors have been derived with the USLE. Other researchers assert that replacing (or modifying) the R_{USLE} factor is only advantageous when runoff is negligible and storms are intense (high infiltration) (Foster, 1982). Although the empirically-based USLE model and its derivatives appear to generally predict erosion well, they were developed for long-term estimates of soil loss and thus appear to be limited in event erosion predictions despite attempts to modify the equation to do so. Many researchers are advocating a new generation of process-based models, such as WEPP (the Water Erosion Prediction Project) and EUROSEM (the European Soil Erosion Model), which have been shown to be superior erosion prediction models (Bhuyan et al., 2002, Stople, 2005).

Baseflow is modeled in SWAT as a linear function of the rate of change in aquifer water height, and recharge is dependent on infiltration of water from the vadose zone. Arnold et al. (2000) used SWAT to examine groundwater recharge and baseflow in a macro-watershed in Mississippi, showing that it performed reasonably well. Chu and Shirmohammadi (2000), however, explain that SWAT cannot accurately simulate groundwater processes because it does not account for groundwater contributions from outside the delineated watershed area (Chu and Shirmohammadi, 2004). This issue was similarly mentioned as a model caveat in karst watersheds (Spruill et al., 2000). It was also noted by Sun and Cornish (2005) that SWAT, when used in arid environments, tended to overestimate runoff, due to its inability to simulate soil cracking effects on hydrology (Sun and Cornish, 2005).

Since its development, many adaptations of SWAT have emerged to improve simulation of specialized processes. For example, in addition to many others, the G-SWAT model incorporates the RUSLE erosion model and includes greater stomatal conductance sensitivity to atmospheric CO_2, while the ESWAT model integrates the QUAL2E model for improved water quality modeling. SWAT has also been successfully combined with the groundwater model MODFLOW (Sophocleousa et al., 1999), in attempt to ameliorate this known limitation of SWAT.

Input Data

Many studies have attempted to quantify the sensitivity of watershed models to variations in input data. Despite the existence of such studies, there still exists, in general, a lack of knowledge about the effects of parameterization variations and input quality of watershed models on sensitivity, calibration, validation, and model robustness (Abbot and Refsgaard, 1996).

The SWAT model requires topographic data, soil characteristics, land-use/land-cover maps, and climatic input data to simulate runoff, and sediment, nutrient, and chemical loading and transport. SWAT first separates the watershed into sub-basins based on topographical features and the stream network. The sub-basins are further divided into Hydrologic Response Units (HRUs) on the basis of soil and land-use/land-cover homogeneity. Each HRU is treated as an individual unit, simulating runoff, erosion and other process at the HRU scale, which are then pooled at the sub-basin outlet. Runoff, sediment, nutrient and chemical yields are aggregated in the sub-basin and then routed through the main channel and to the watershed outlet.

In SWAT, a DEM, land-use/land-cover maps, and soil characteristics are used for watershed delineation, stream-network generation, and ultimately to divide the area into sub-basins and HRUs. Reducing the mesh-size (spatial resolution) of this input data, which are represented in grid-format, often results in high prediction errors, chiefly due to inaccurate estimations of landscape attributes (Thompson et al., 2001, Chaplot et al., 2000). Studies have shown that both the resolution and the aggregation of such data may considerably affect model performance (Becker and Braun, 1999).

Chaubey et al. (2005), in an analysis of streamflow and nutrient output in a large, mid-western agricultural watershed, determined that decreasing DEM resolution yielded lower streamflow predictions in SWAT. They further indicated that a DEM resolution of 100 to 200 meters can be considered a reasonable input resolution, yielding less than 10% error (Chaubey et al., 2005). Conversely, Chaplot (2005), employing SWAT in a similar sized agricultural watershed, ascertained an upper limit DEM resolution of 50 meters required for accurate simulation of monthly runoff and sediment yield predictions. Furthermore, the Chaplot asserts that a detailed, precise soil map is imperative for sediment and nutrient predictions; although little sensitivity to soil map resolution was found for runoff generation (Chaplot, 2005).

While the DEM resolution is undoubtedly important for model performance, soil and land-use/land-cover map resolution can also influence model output accuracy. Luizio et al. (2005) found that variations in soil map resolution show a moderate insensitivity to generated runoff and sediment yield output, with the exception of the K_{sat} parameter (Luzio et al., 2005). In particular, the authors emphasize the increasing importance of high-spatial resolution data with decreasing watershed size (Luzio et al., 2005). Conversely, Romanowicz et al. (2005), in an analysis of SWAT sensitivity in a small agricultural catchment in Belgium, suggest that SWAT sediment prediction is very sensitive to soil data as well as land-use input data (Romanowicz et al., 2005). Likewise, Luzio et al. (2005) show that low resolution land-use/land-cover maps, in general, greatly affect sediment yields, but not runoff estimates. The apparent sensitivity of sediment loading – as opposed to runoff – to land-use/land cover and soil data may be attributed to the number of HRUs which are defined by coarse-resolution data.

Many studies have revealed that variations in the size of HRUs, the basic unit for modeling processes in SWAT, have little effect on flow predictions but substantially affect sediment, nutrient and chemical loadings and transport (Bingner et al., 1997, Jha et al., 2004, Geza and McCray, 2007, FitzHugh and Mackay, 2000). FitzHugh and MacKay (2000) illustrate that this is a result of the non-linear sensitivity of the MUSLE (Wischmeier and Smith, 1978) runoff term to changes in area, due to its relation with the peak runoff model used in SWAT. This is calculated with the rational method (Kuichling, 1889). Conversely, the runoff production process, which is associated with the CN parameter and determined by the SCS curve number method, has no sensitivity to changes in area because the area-weighted mean of the CN parameter does not change with HRU area.

Comparative Model Performance

There are many other distributed models that simulate comparably to SWAT, particularly with respect to their spatial and temporal scales and their ability to model the effects of management practices in large agricultural watersheds. These include the Hydrological Simulation Program – Fortan (HSPF) (Bicknell, 1993), MIKE-Système Hydrologique Européen (MIKE-SHE) (Refsgaard and Storm, 1996), and Annual Agricultural Non-point Source Pollution model (AnnAGNPS) (Young et al., 1987, Bingner and Theurer., 2001) and their various permutations (slight modifications using the same model framework). While other models do exist, such as ANSWERS (Beasely et al., 1980), TOPMODEL (Beven and Kirkby, 1979) or WEPP (Laflen et al., 1991), these have been developed to simulate processes on smaller time and spatial scales (i.e. hillslopes or instantaneous flood events). Because the purpose of this study is to modify a watershed scale model, only other comparable models are reviewed.

Borah and Bera (2003), in a review of eleven watershed-scale models, and Merritt et al. (2003), in a review of seventeen erosion and sediment transport models, comparatively examined the mathematical bases and applications of SWAT, MIKE-SHE, AnnAGNPS, and HSPF or their derivatives (Borah and Bera, 2003, Merritt et al., 2003). MIKE-SHE is a fully distributed model and, because of its high input demands, is recommended for simulations in small watersheds where detailed input is available. MIKE-SHE uses a diffuse wave equation to simulate flow routing and works on a sub-daily time step; it is, therefore, able to simulate both single (flood) events and over long time periods. Conversely, SWAT and AnnAGNPS, because they run on a daily time step, are unable to simulate single events. MIKE-SHE simulates sediment transport and deposition as one-dimensional physical process using an advection-dispersion equation. The distillation of the three-dimensional sediment movement process is, according to Merritt and colleagues, a weakness of the model and makes its use questionable for long term puposes. Despite these reservations, El-Nasr et al. (2005) have shown that both SWAT and MIKE-SHE were able to perform comparably for long-term annual simulations in a Belgian agricultural watershed, although MIKE-SHE tended to better model streamflow variations (El-Nasr et al., 2005).

Conceptually, AnnAGNPS and SWAT are similar in that their hydrological components, and nutrient transport and erosion processes are adapted from the GLEAMS and EPIC models, among others. Both models employ the SCS curve number method and derivates of the USLE to simulate runoff and erosion, respectively. They also appear to perform with similar results (Das et al., 2007).

SWAT has been extensively compared with HSPF because they are each components of the BASINS (Better Assessment Science Integrating Point and Non-point Sources) system, a program created for modeling and environmental decision-making in the United States. Aside from the comparative ease of SWAT model calibration when compared with HSPF (Saleh and Du, 2004, Nasr et al., 2003), studies have shown that SWAT is better able to simulate varying climatic conditions and nutrient loading and transport (Van-Liew et al., 2003). On the other hand, studies examining flow have found conflicting results for different regions. For example, in Indiana SWAT was able to better simulate lowflow (Singh et al., 2005), while in Ireland HSPF was found to be superior in lowflow simulations (Nasr et al., 2003).

SWAT appears to be suitable for simulations in agricultural watersheds (Van-Liew et al., 2003, Borah and Bera, 2004) while HSPF is more accurate in urban areas (Im et al., 2003). These differences may be due to the lumped, conceptual-based nature of HSPF and the equations used to determine flow and sediment generation. The storage based, non-linear reservoir equation employed in HSPF to calculate flow assumes a leveled water surface over the channel and cannot represent wave-forms; consequently, it is more appropriate for routing in lakes and reservoirs (Borah and Bera, 2003). Conversely, the SCS curve number method calculates runoff using daily water budget components. A weakness to this model is that it relies heavily on calibration with observed data for parameterization (Walton and Hunter, 1996). Furthermore, the soil profile in HSPF is considered to have only an upper and lower storage layer, below which water percolates into the groundwater system; while SWAT is able to simulate infiltration and percolation through up to 10 distinct soil layers using one-dimensional saturated flow rates.

After considering the relative performance and utility of these four models, Borah and Bera (2003) conclude that SWAT is a promising model for management and decision-making in primarily agricultural watersheds. Merritt et al. (2003) on the other hand, strongly urge modelers to circumspectly make their choice, based on the needs of the project and do not identify any one as particularly advantageous.

SWAT Model Applications in the Tropics

There are relatively few peer-reviewed, published SWAT model applications in tropical regions (Gassman et al., 2007), which is unsurprising considering the heavy occidental bias on publication access. This makes a comparative analysis of SWAT model performance in the tropics difficult, particularly because soils, species and climate are generally more diverse and varied than temperate zones (El-Swaify et al., 1982). Thus, only a short résumé of these applications is feasible.

SWAT has been applied in many tropical regions as a support system for environmental management decision and policy making. SWAT was successfully used by Singh and Gosain (2007) to implement an inter-state water allocation program in India to conserve water resources (Singh and Gosain, 2007). Schuol (2007), used SWAT to identify regions of potential water scarcity in West Africa, providing a regional perspective of water flows (Schuol et al., 2007). In addition to its ability to aid crucial environmental policy making, these two examples provide evidence to suggest that SWAT may be useful for analysis of tropical basins at regional scales. SWAT has also been applied, with acceptable performance, to model the effects of hypothetical land-use change scenarios (primarily deforestation and reforestation of croplands) on flow, sediment, and nutrient yields in

Honduras (Rivera and Martinez, 2003), Costa Rica (Benavides and Veenstra, 2005), Brazil (Barsanti et al., 2003), Kenya (Jacobs et al., 2003a, Jacobs et al., 2003b), and China (Ouyand et al., 2007). In Kenya and China, SWAT was used to quantify the impacts of cropland reforestation on water and sediment yields for watershed protection policy implementation.

Despite the modest amount of literature on SWAT applications in the tropics, large international organizations, such as the World Bank and FAO, endorse this model for use in developing (mostly tropical) countries (Tognetti et al., 2004, Fulcher et al., 1997). Likewise, many institutions in the tropics appear to favor this model because it is a public software package and it boasts the ability to simulate in large un-gauged or data-scarce regions.

Model Selection

A comprehensive model, able to adequately and reliably predict water flows and erosion production in the PCW would be an advantageous tool to support watershed management, conservation, and decision-making activities. The ACP and researchers have recognized the need for such a model (Ibáñez et al., 2002), however they have focused principally on the benefits provided by forested regions and at small scales (i.e. water flow timing/amount and erosion control on hillslopes or in micro catchments of < 1 km^2) (Niedzialek and Ogden, 2005, Kinner and Stallard, 2004). Although these are clearly important components, any model used in the PCW must also account for the additional, and perhaps increasingly influential, factors that can also affect water flows and erosion. These include the effects of land-use change, such as the extensive reforestation of the PCW expected to be completed by the year 2020 (most of which will be pasture converted to forestry projects) or the drastic amplification of pineapple production projected to continue increasing in the TCH basins (Martez and Vergara, 2004). The ability to account for the seasonal variations of flow and erosion production is also of paramount importance. Other factors to be considered are the meteorological variations due to climate change and/or El Niño events, the mounting water and (hydrogenerated) electricity consumption in the PCW (Ibáñez et al., 2002), and the relationship of the socio-economic context and decisions made by land-users.

SWAT was chosen as an appropriate tool for this study for two reasons. Firstly, the establishment of the SWAT and GIS databases will help build a foundation for continued or supplemental research in the TCH basins, making this a beneficial and, most importantly, practical tool for IDIAP and other institutions. Secondly, the SWAT model may be expanded upon in future research endeavors to cover other basins or the entire PCW. Other physical processes (such as agrochemical or nutrient loadings), other crops grown in the PCW (such as rice, corn, or commercial tree species), rural and urban water consumption, and reservoir sedimentation may also be included in future modeling activities. The SWAT model may be combined with climate change models (Eckhardt and Ulbrich, 2003, Stone et al., 2001, Hanratty and Stefan, 1998), or linked with socio-economic models to assess the relationship between biophysical and economic factors and their impacts on different land-use practices (Urama et al., 2006, Whittaker, 2005, Coiner et al., 2001, Lant et al., 2005, Breuer et al., 2006). These are all pertinent to the context of the PCW.

3.4 Pineapple Cultivation

The pineapple (Ananas comosus) is an herbaceous, perennial monocotyledonous plant native to tropical America which can be easily grown as a commercial crop in the tropics because of its many unique features. Of principle importance is the plants' resilience to drought due to its CAM metabolism, which exhibits high amounts of nocturnal transpiration – when temperatures are cool – thereby limiting water loss during transpiration (Cote et al., 1993). The plant is also tolerant to soil acidity and has therefore been recommended by FAO (2005) as a good crop to grow in Acrisol soils, which often suffer from aluminum toxicity.

Erosion Control in Pineapple Fields

Erosion control measures are especially pertinent to seasonal crops, such as the pineapple, which can have high soil disturbance rates relative to plantations or pastures (disregarding livestock impacts). In addition to soil characteristics and climatic conditions, land management practices can contribute to soil erosion prevention or exacerbation in any agroecosystem. Given the circumstances of the PCW and its vulnerability to increased reservoir sedimentation, soil conservation techniques must be employed on pineapple farms in the TCH if sediment yields are to be controlled. Several methods may be applied to agricultural landscapes, such as mulching, planting along contour lines, terracing, among others, that can effectively reduce erosion by minimizing raindrop impact and/or retarding surface runoff velocity (Lal, 1990).

Mulching, which covers soil with a protective layer, has successfully reduced erosion in pineapple fields. Plastic mulch, a widely used mulching material, was the most effective erosion control measure in Hawaii (Wan and El-Swaify, 1999). Organic residues (biomass), such rice husks, have been successfully used in Asia (Sarma and Medhi, 1997); while green mulching materials (cover crops), such as cassava (Manihot esculenta) or pigeon pea (Cajanus cajan) have been applied on pineapple farms in South America (Montilla and Catayo, 1995). In addition to reducing the vulnerability of soils to erosion, mulching with almost any material increases pineapple fruit yield when compared to bare soils (Kuruvilla et al., 1988, Obiefuna, 1991, Dominguez et al., 1995). Mulching increases plant growth efficiency (Rebolledo-Martinez et al., 2005) by increasing soil humidity, organic matter, and nutrients (with biomass mulching) (Montilla and Catayo, 1995).

When farming sloping lands, planting along contour lines or on terraces are common methods used to manage erosion because they direct runoff flows and reduce runoff velocity. On extreme slopes, however, these measures alone may not be the absolute solution to erosion control. In Taiwan, researchers found that cultivating pineapples at high planting densities, with biomass mulch, and along contours reduced erosion 13 fold and runoff by 8 fold compared to straight up and down planting patterns (Liao and Wu, 1987).

Crops or vegetation planted around the border of an agricultural field can also reduce erosion. In the TCH basins, strip barriers or hedges, which consist mostly of grasses such as citronella grass (*Cymbopogon nardus*), lemon grass (*Cymbopogon citrates*), or koronivia grass (*Brachiarua humidicola*), are one of the few erosion prevention measures employed, although used only by 17% of pineapple producers (Martez and Vergara, 2004).

As a shade tolerant plant, the pineapple crop has been successfully incorporated into agroforestry systems. Such systems include combinations of pineapple with coconut trees, banana trees and other fruit trees, and coffee, palm oils and other tropical cash crops (Dijk, 1987, Achard et al., 2004, Prinz and Rauch, 1987). Furthermore, agroforestry with pineapple plants has been associated with the amelioration of soil properties, such as nutrient and organic matter content and soil fauna activity (Saha et al., 2005, Peng et al., 1999), which can potentially reduce erosion by enhancing infiltration and soil structure.

Beyond land management, mechanical disturbances can also significantly contribute to erosion and must be considered in erosion prevention planning. The primary source of erosion in Hawaiian pineapple fields is due to dirt roads and tillage practices during the early growing season (El-Swaify et al., 1993). The erosion production on dirt roads may be partially attributed to the soil disturbance caused by vehicles as well as the two to three fold increase in runoff potential (Curve Number values) when compared to those of pineapple fields alone (Cooley and Lane, 1982). While roads contribute to erosion, altering or eliminating tillage practices can reduce erosion in pineapple fields up to 1/14 the levels associated with conventional tillage (Sugahara et al., 2001).

In sum, the different erosion prevention techniques, outlined above, have various advantages and the technique(s) used should be tailored to the local conditions. In many cases, a combination of erosion prevention techniques will be the most sustainable choice. For example, because the pineapple canopy, after closure, provides soils with protection from erosion causing agents and reduces runoff potential (Obiefuna and Asoegwu, 1993) (Cooley and Lane, 1982), methods such as mulching would appear to be most imperative at the commencement of the pineapple crop cycle and may, in fact, become increasingly less effective as crop canopies mature. Similarly, planting vegetation around the border of fields (as done in TCH) may only marginally reduce erosion (Sugahara et al., 2001), implying that a combination of techniques is likely the best means to maximizing erosion prevention on pineapple fields.

3.5 Ecosystem Services

In order to place this research under the context of a PES pilot project, a definition of ecosystem services is provided, followed by a brief explanation of PES mechanisms and their applicability to the PCW.

Payment for Ecosystem Services

A promising conservation program, PES, is expected to be implemented in the TCH basins and will attempt to provide both pastoralists and farmers with incentives to use soil conservation techniques. The TCH basins are just one of many areas that will take part in a PES pilot project to assess the feasibility of applying such a program in the greater PCW. In order to describe the inner-workings of the PES mechanism, a definition of ecosystem services must first be given. The Millennium Ecosystem Assessment (MEA) defines ecosystem services as the benefits people obtain from ecosystems. These can be broadly subdivided into 4 categories: (i) provisioning services, which are products obtained from the ecosystem; (ii) regulating services, which are benefits obtained from the regulation of ecosystem processes; (iii) cultural services are the non-material benefits provided by ecosystem services; and (iv) supporting services, which are the services essential to production of all other services (MEA, 2005). According to the MEA, the high demand for ecosystem services has resulted in trade-offs among the benefits received; for example, the conversion of forested land to an agricultural field will increase provisioning services, such as food supply, but may decrease regulatory services, such as water regulation and quality or erosion control.

The concept of PES merges markets with ecosystem services to provide economic incentives for resource conservation. The PES mechanism functions in a manner whereby beneficiaries of ecosystem services remunerate the service providers, in this case pineapple growers and ranchers, for conserving soil and water resources. In the PCW, regulating and provisioning services, such as flow timings, erosion control and fresh water provisions, are vital services that could be conserved via a PES mechanism. Service buyers, such as the ACP, could pay pastoralists and pineapple farmers for adopting management practices that reduce erosion. Decreased erosion would reduce the amount the ACP spends on dredging operations, thereby freeing up funds that could be used to reimburse the agriculturalist for the costs of erosion control. The benefits of the erosion-prevention measures should outweigh the costs of dredging operations and payments must surpass the opportunity cost of land. Other versions of this scenario can be explored, for example water consumers paying farmers (via a user tax) to reduce fertilizer use to improve water quality or the government providing incentives to reforest land to improve dry season flow and reduce erosion, and many others. (See Fotos et al., 2007 for a detailed assessment of demand for ecosystem services in the PCW).

In the context of the expanding pineapple culture in the TCH basins and the looming threat of increasing sedimentation of Canal reservoirs, sustainable agroecosystems are a necessity and are attainable; yet the information, resources, and incentives must be simultaneously provided to farmers and ranchers in order to encourage such changes to occur and solidify. Moreover, a practical tool is needed to predict the effects of the current pineapple cultivation practices and to simulate the potential impact of the above-mentioned erosion prevention measures; this will support the incentive-based conservation method which may help reduce sediment yield in the TCH basins.

4.0 Materials and Methodology

The subsequent section first describes the input data used for the construction of the SWAT model and secondly, it provides an explanation of SWAT model set-up and simulation, calibration and validation, and sensitivity and uncertainty analyses and procedures. Although much of the data necessary for SWAT is available at the tri-basin level (THC), observed streamflow and sediment yield (necessary for calibration) only exist for the CQ basin. As such, only the CQ basin was able to be modeled. In this section, the input data used for SWAT is described for the TCH (as it was input into SWAT). The delimitation of the CQ basin for modeling was then undertaken during the model set-up procedures (Section 4.2)

4.1 Input Data

SWAT input data may be divided into two general categories, spatial input, which includes physical landscape data such as topography, water body location, and land-use/land-cover and soil maps, and temporal input, which includes climatic data used for model simulation and flow and sediment records used for model calibration and validation. The following section presents the generation and modification of all SWAT input data. Spatial data was modified with ArcGIS 9.2 and conforms to the Universal Transverse Mercator (UTM) coordinate system and the North American 1927 (NAD27) reference datum.

Topography and Water Bodies

Topographical features of the TCH area are represented by a grid-based 30-meter vertical resolution DEM, provided by ACP (2006) (Map 2b, page 10). Rivers and their tributaries are represented by a vector-based stream network (Map 1, page 9) also provided by ACP (2006).

Land-use/land-cover Map

The land-use/land-cover map employed in SWAT was generated from three individual map sources. Two digital maps (polygon-based) of areas under pineapple cultivation, generated by the ACP from Landsat-7 images of June 2003 and October 2006, were overlaid with a third digital map of land-use/land-cover in the TCH area. This map was generated by the ACP with Landsat-5 imagery from the year 2000. Land-use/land-cover in the third map resource was classified as urban, forest plantation, mature and secondary forests, pasture, and agriculture, according to the ANAM classification system (ANAM and ITTO, 2003). Once the three maps were overlaid, land-use/land-cover was reclassified according to the following 5 categories: areas in pineapple cultivation (a) in 2003 only, (b) in 2003 and 2006, and (c) in 2006 only, (d) pasture cover, and (e) forest cover (Map 2a, page 10). The forest cover class is an aggregate of forest plantations, primarily teak trees, and mixed low-land mature and secondary tropical forest, which principally exist in small patches along riparian zones and as divisions between pastures and agricultural crops.

Soil Map

Soil physical characteristics, represented by a soil map, are required SWAT input. In the TCH basins, soil data of adequate detail able to meet the soil parameter input criteria is not available. However, minimal data was able to be extracted from two nation-wide soil surveys, one by conducted by IDIAP (1996) and the other by CATAPLAN (1970), which was used to estimate the required soil input parameters.

The IDIAP (1996) soil survey involved the classification and mapping of soil physical and chemical characteristics, including pH, organic matter content, trace metals and elements, nitrogen, phosphorus and potassium concentrations, and soil texture (IDIAP, 1996). Soil sample data was interpolated using the inverse distance weighting method, yielding a continuous raster map of Panama with 200m^2 resolution. In the TCH basins, where eight soil samples were taken, interpolation resulted in more than 1800 cells and over 400 distinct soil texture combinations, some varying by a fraction of a percentile (representing percent weight) in a particular textural component. In order to facilitate the estimation of other required SWAT soil parameters, as describe below, the number of distinct soil texture combinations (individual cells) was reduced. Soil texture data was graphed and spatially aggregated according to emergent groupings (Figure 2). Aggregated groups were assigned the mean percent weight of sand, silt, and clay of all points within the group.

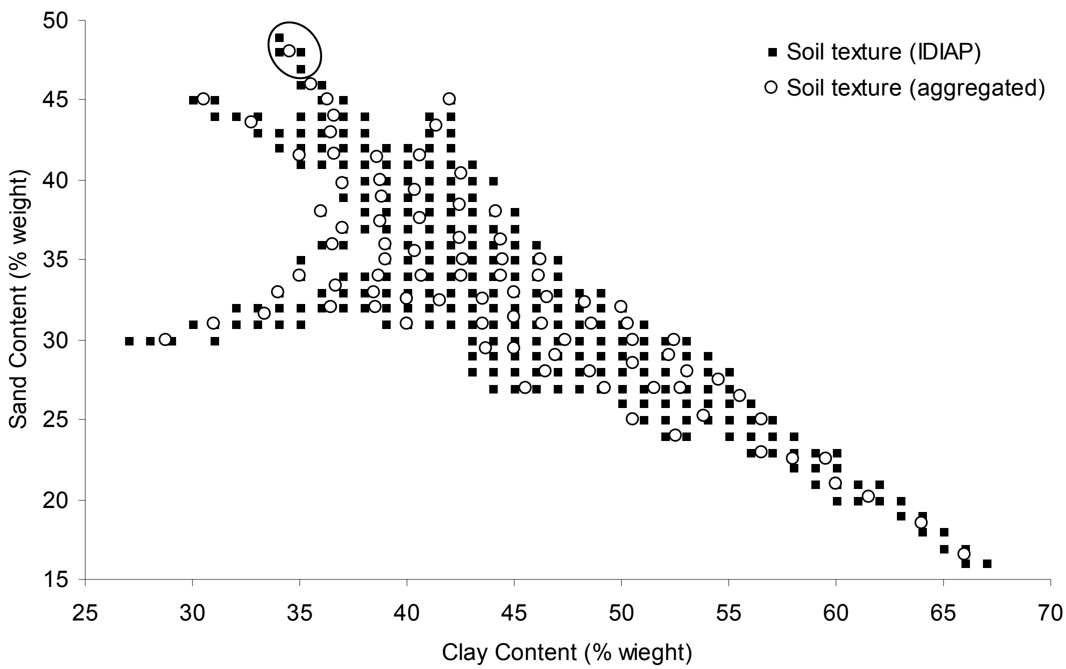


Figure 2: Scatter plot of clay and sand content of soils in the TCH basins, from IDIAP (1996); the uniformity of the points is due to the interpolation procedure. The large circle indicates a salient example of data points which were aggregated into a single textural grouping.

Soil texture was then used as the basis to estimate other soil parameters using pedotransfer functions (PTFs), equations derived from statistical regression analyses of known soil properties. PTFs may be used to approximate soil hydraulic characteristics based on soil texture and, if available, bulk density, organic matter, or soil water retention, the inclusion of which can improve model accuracy (Saxton and Rawls, 2006). Textural data was employed in the Soil and Water Characteristics model (Saxton and Rawls, 2005), a program that calculates soil hydraulic properties based on equations derived from statistical correlations of known USDA soil data. The minimum required input data (soil fractional sand and clay content, gravel content, and organic matter; Map 3, page 41) was readily available from the IDIAP soil survey database, thereby making this program a suitable choice. The program also provides a single interface from which estimates for saturated hydraulic conductivity (Ksat), bulk density (BD), and available water capacity (AWC) may be simultaneously generated. Estimated parameters (Table 1) were then integrated into the soil map using GIS software.

Table 1: Critical Statistics for the soil hydraulic properties derived from PTFs.

Parameter	Mean	Standard Deviation	Range
Ksat (mm/hr)	274.5	45.56	208.9 – 326.5
BD (g/cm^3)	1.731	0.066	1.536 – 1.872
AWC (mmH$_2$0/mmsoil)	0.110	0.0174	0.055 – 0.165

SWAT also requires soil organic carbon content. Although IDIAP (1996) did not quantify this parameter, organic matter content data was available. The following equation, extracted from the SWAT user manual (Neitsch et al., 2002) for use in the USLE soil erodibility factor (K) equation (Wischmeier et al., 1971), was employed for soil carbon content calculations:

$$orgC = \frac{OM}{1.72}$$

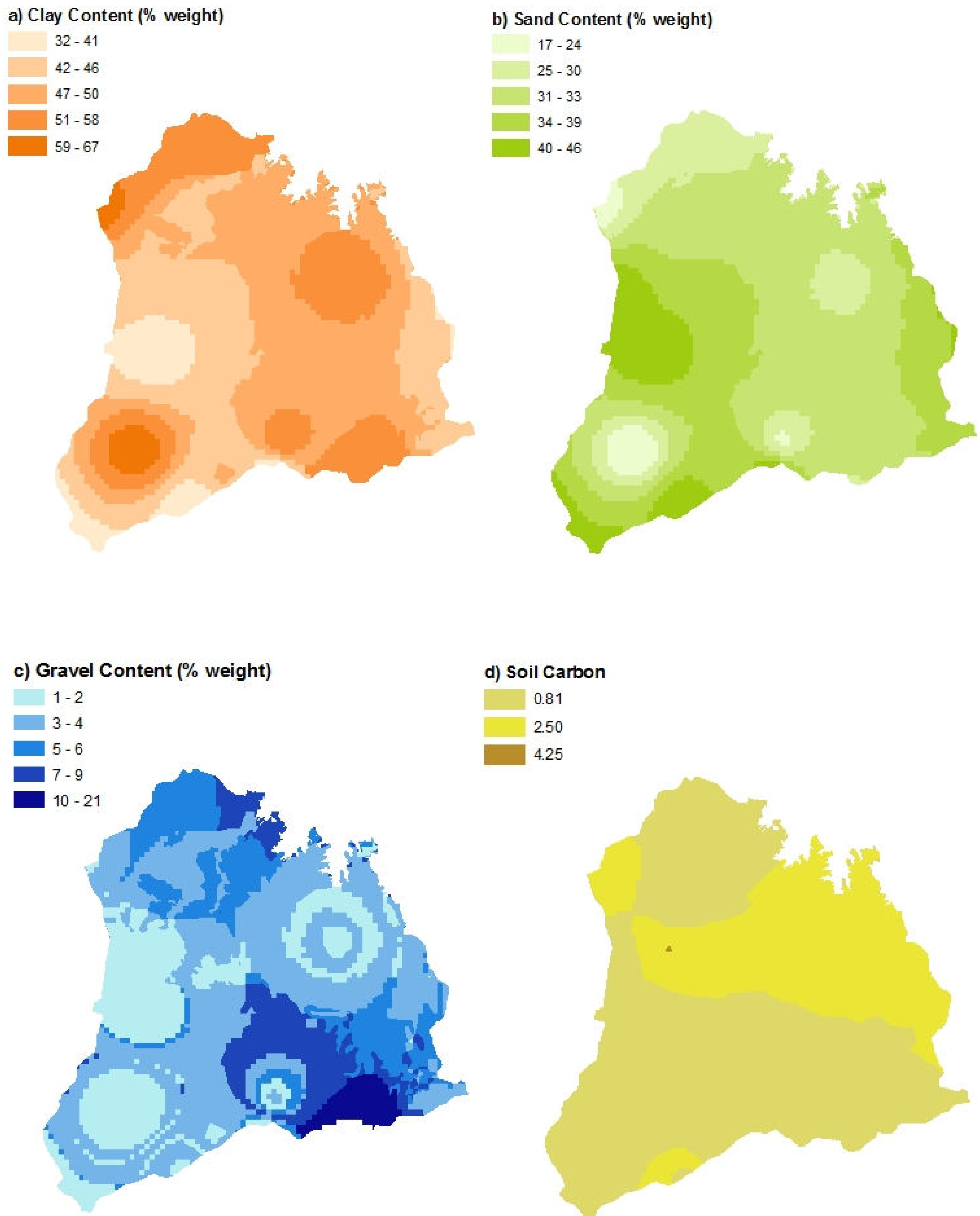
Where orgC is percent organic carbon content and OM is percent organic matter. IDIAP (1996) classified organic matter as high, medium, or low, corresponding to a percent weight range of 0.0 – 2.9%, 3.0 – 5.9%, and 6.0 – 9%, respectively. The median organic matter content of each range was determined, transformed into organic carbon content using the above equation (Map 3, page 41), and incorporated into the soil map using GIS software.

The second soil survey, performed by CATAPLAN (1970), was used to estimate two other input parameters needed for the SWAT soil map, soil depth and soil hydrologic group. This information was procured from the ACP (2006). The CATAPAN maps (1:100,000), classify land according to the following categories: soil taxonomy, epipedon, endopedon, parent material, slope, drainage class, texture, erosion extent, stoniness, soil depth, and land-capability – or recommended land-use (CATAPAN, 1970). Each category has a description explaining the criteria upon which soils were classified. For example, soils in the THC are classified as either 'fine clay', which are "[soils with]…more than 30% clay but no less than 60% clay", or as 'clayey skeletal', which are "[soils with]…more than 50% by volume coarser than two millimeters with enough fines to fill interstices larger than one millimeter. The fraction less than two millimeters is as defined for fine clays" (CATAPAN, 1970). Although the CATAPAN maps provide an effective reference guide for land-use planners, the bulk of definitions and the classification system employed do not provide the precision needed for use in a distributed model. Soil depth and soil drainage class, however, were able to be modified and used for the soil map construction (Map 4, page 42).

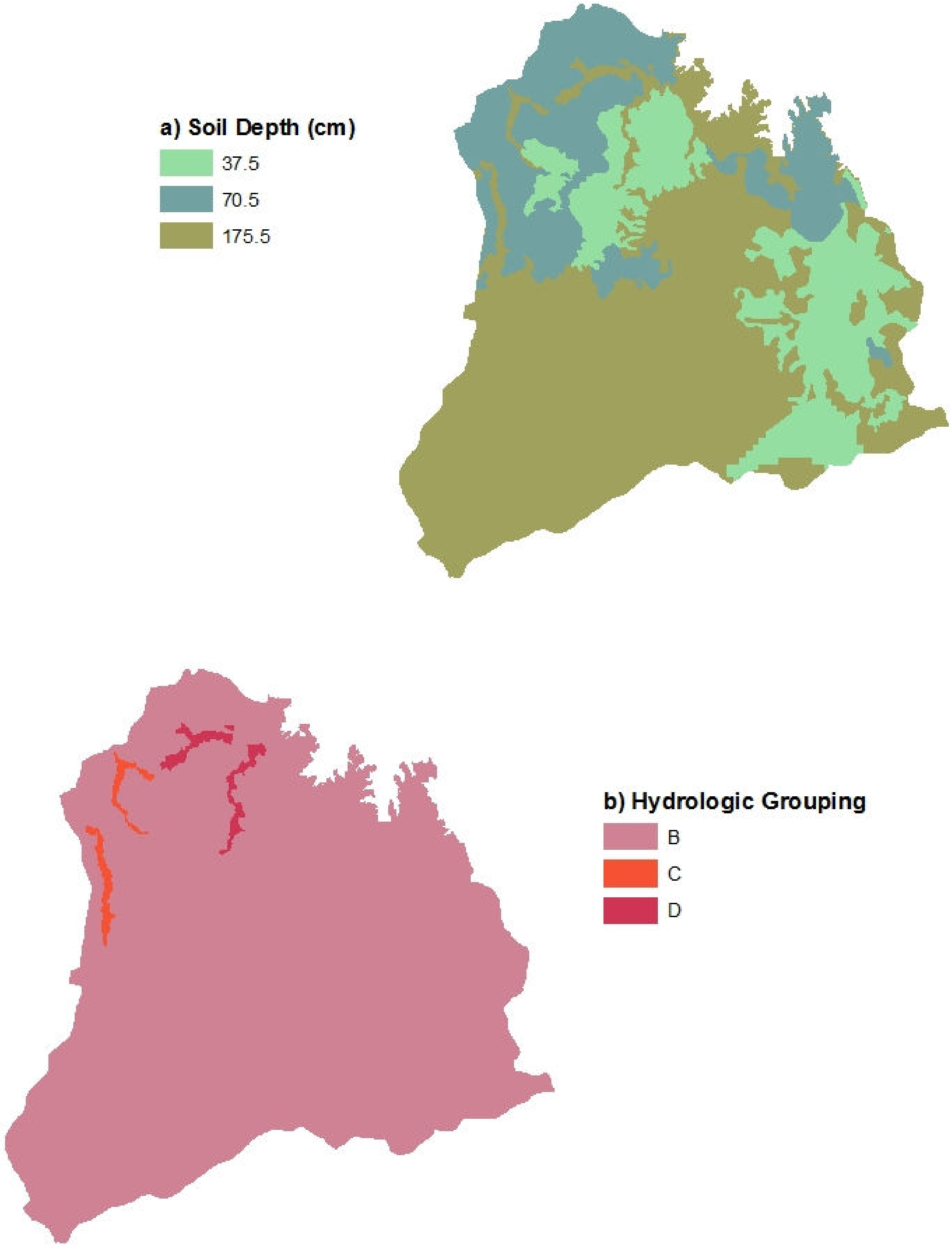
Soil depth, according to CATAPAN, is defined as the total depth of the soil profile favorable for root development and includes substrata in most soils. Soils are classified according to five different categories, each with a range of soil depths. The median of each depth range was calculated and incorporated into the SWAT soil map. Averaged soil depths in the TCH area ranges from 37 to 175 centimeters; more than 70% of soils in the "moderately deep" category (Map 4, page 42).

Similarly, CATAPAN categorized soils according to drainage class, each of which is adjoined with a description of the soils' infiltration characteristics. Each of the descriptive drainage classes described by CATAPAN is similar and comparable to the soil hydrologic groups as described by the USDA Soil Survey and NRCS as outlined by Neitsch et al. (2002). Although soil hydrologic groups may, in fact, be determined empirically (based on permeability and shrink-swell potential), no such data on soil hydrologic properties was available for the study area; therefore the subjective definitions, as defined by USDA/NRCS and CATAPAN, were used as a reference for conversion from drainage class to a corresponding hydrologic group (Appendix I, Table 3). Soil depth and soil hydrologic groups were merged with the soil map using GIS software.

SWAT is able to integrate and model up to 10 soil layers, each with distinct soil characteristics. However, such data is not yet available for the TCH region, thus for modeling purposes it is assumed that soil characteristics are uniform throughout the entire soil profile.



Map 3: IDIAP soil-survey data used to construct the SWAT soil map and to calculate PTF-derived soil hydraulic properties.



Map 4: CATAPAN soil data used for SWAT soil map construction.

Streamflow and Sediment Data

Stream flow and suspended sediment, used for model calibration and validation, have been monitored daily since 2003 at one gauge station near the outlet of the Caño Quebrado River (CQ1) (Map 1, page 9). This monitoring station covers a drainage area of 67 km^2, which corresponds to 90% of the Caño Quebrado River basin, accounting for 42% of the entire study area.

Baseflow at the CQ1 station was calculated with streamflow data from 2003 to 2006, using the following recession filter as described by Nathan and McMahon (1990) and recommended by for use in SWAT (Neitsch et al., 2002):

$$q_t = \beta \cdot q_{t-1} + \frac{1+\beta}{2} \cdot Q_t$$

Where q is the filtered runoff at time t, Q is the flow, and β is a filter coefficient equal to 0.925. The filter may be passed through the dataset once forward, then backward, and then forward again. An average of the second and third passes through the filter was determined and used as an estimate of baseflow. Figure 3 shows the resultant baseflow separation.

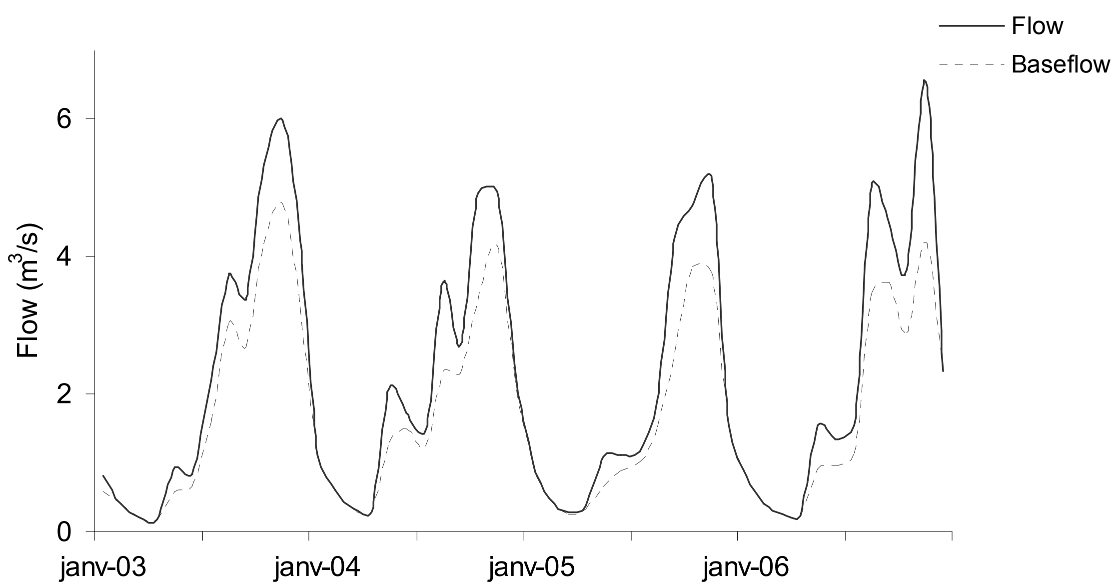


Figure 3: Monthly average flow at CQ1 and derived baseflow for the years 2003 to 2006.

Climatic Data

SWAT requires daily climatic data for simulation. Precipitation in the TCH basins is monitored daily at two stations and a third station is located just outside the western border (Map 1, page 9). Daily precipitation at each station has been recorded for different time periods: Cerro Cama (CCA) has been monitored for 10 years, Zanguenga (ZAN) for 2.5 years, and El Chorro (CHR) has been monitored for 25 years. Data from all three stations was used for model simulations in SWAT.

In addition to daily precipitation, SWAT also requires daily maximum and minimum temperature, solar radiation, relative humidity and wind speed for simulations. These data may be generated in areas where climatic information is incomplete or non-existent, such as in the TCH basins, using the WXGEN weather generator model (Sharpley and Williams, 1990). WXGEN is a mathematical model that estimates daily climatic input through statistically generated data from at least 20 years of daily observed values. In the greater PCW, there are three stations which have more than 20 years of daily meteorological records available, two of which, Balboa (BAL) and Gamboa (GAM), are in close proximity to the TCH basins (Map 1, page 9). GAM station, which is slightly closer to the TCH area, is located in a forested zone, while BAL is located in a semi-urban area.

Monitoring of precipitation at the ZAN station began in May 2004; accordingly, precipitation had to be generated at this station to complete the annual record for model calibration procedures (see section 4.3). Given that the weather generator is a reliable predictor of climatic data only over long time periods (> 10 years) and that the time period of observed streamflow and sediment data is relatively short (from 2003 to 2006), it was decided that precipitation at the ZAN station should not be estimated using the weather generator for model calibration/validation procedures. Instead, missing data was completed using precipitation records from the CCA station from before May 2004. The CCA station was chosen, as opposed to the CHR station, because precipitation amounts and storm events observed at the CCA station are more correlated with those observed at

ZAN than those observed at the CHR station (Figure 4). All other climatic data was estimated using the weather generator.

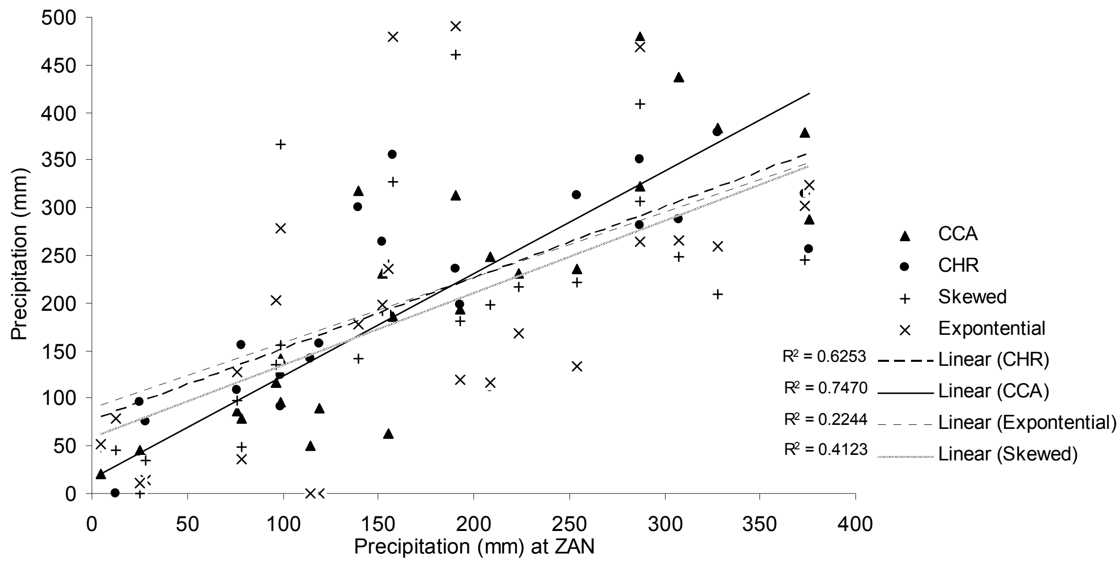


Figure 4: Total monthly precipitation at stations CCA and CHR plotted against total monthly precipitation observed at the ZAN station. All years of available data are presented (CCA = 10 years; ZAN = 2.5 years; CHR = 25 years). The coefficient of determination, r^2, corresponding to each regression line is shown.

Land Management Practices Data

Land management practices, such as planting and harvest schedules, tillage practices, fertilizer applications etc., are required by SWAT when the effects of land management practices on physical processes is to be examined. Accurate simulation of these practices is important for studies that desire to simulate erosion and, if applicable, nutrient and agrochemical transport and water resource use. The land management practices performed by pineapple producers in TCH, outlined in Appendix II, were incorporated into the SWAT model. Land management practice data was procured from IDIAP interviews (2007, unpublished) with 50 willing-to-participate pineapple producers in the TCH region, representing approximately half of the pineapple producer population in the area.

In addition to land management practices, it was decided that land-use change dynamics should to be integrated into the SWAT model to consider the noteworthy expansion of pineapple cultivation between the year 2000 and 2006 (Map 2a, page 10). This was incorporated into the model through the aforementioned land classification, but where pineapple cultivation was divided according to areas in production in (a) 2003 only, (b) 2003 and 2006, and (c) 2006 only. All areas are considered to be pasture cover prior to land conversion.

Pineapple Crop Growth Simulations

Data on more than 90 different plant species are available for SWAT plant growth and crop yield simulations including grasses, shrubs, trees, and most major commercial crop species such as corn, wheat, soy etc. The data necessary to simulate growth is stored in the SWAT default crop growth database but does not include information on the pineapple plant. Information necessary to simulate pineapple plant growth was, therefore, gathered from current literature according the criteria as outlined by Neitsch et al. (2002). All data used for pineapple plant growth simulations is summarized in Appendix I, Table 4 and model validation procedures and results are discussed in Appendix II.

4.2 SWAT Model Set-up and Simulation

Watershed Delineation

The ArcView-SWAT model interface has an automatic watershed delineation tool which partitions large watersheds into smaller drainage subunits, or sub-basins. The grid-cell method, used by SWAT and other models, is based on the DEM input and allows more spatial detail to be integrated into the model, which is beneficial for large heterogeneous watersheds.

Initially, the TCH basins were manually delineated using the preexisting sub-watershed boundaries of the PCW as defined by the ACP. Within the TCH basins, sub-basins were delineated using the automatic delineation tool. As part of the initial delineation process, all "sinks" in the DEM were filled so as to remove any internal drainage areas or reservoirs which do not actually exist, but may be incorrectly represented by the DEM. Following this, the main watershed outlet was manually defined as CQ1. This allows SWAT to identify the area contributing to flow using the outlet as a reference point and thereby isolated the CQ basin from the others. Stream flow direction and drainage networks were then determined by employing a flow direction function on the DEM input, which was automatically compared with the vector-based stream network to improve delineation accuracy. Subbasins were then assigned according to the derived drainage networks, resulting in a total of 37 subbasins within CQ.

Following sub-basin delineation, each subbasin was divided into Hydrologic Response Units (HRUs), defined according to unique land-use/land-cover and soil type combinations. HRUs were divided according to the resolution of the 30 meter DEM, yielding a total of 274 distinct HRUs across the study area (Figure 5). Non-major land-uses, such as the subsistence agriculture present in the area (Map 1, page 10) are absorbed into major land-uses (such as pineapple crops or pasture) during the division. HRUs are the basic building block of the SWAT model and most processes are modeled at this level, including runoff and erosion.

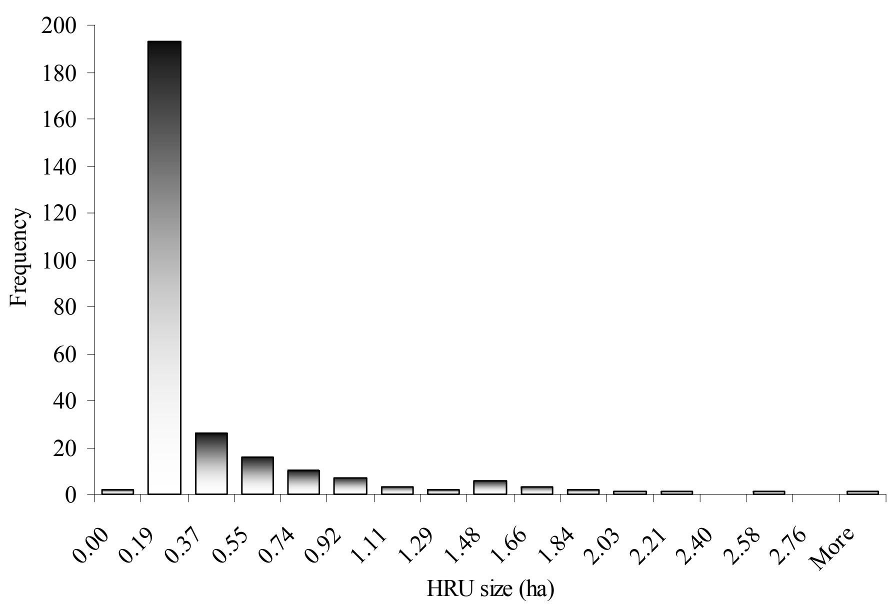


Figure 5: Size distribution of the 274 HRUs.

Model Set-up

SWAT offers three options for modeling potential evapotranspiration, the Hargreaves method (Hargreaves and Samani, 1985), the Penman-Monteith method (Allen, 1986, Allen et al., 1989, Monteith, 1965) or the Priestley-Taylor method (Priestley and Taylor, 1972). Choosing the correct model is imperative for achieving an accurate model representation (Kannan et al., 2007). The Penman-Monteith model for estimating evapotranspiration rates has been successfully applied in tropical catchments in Panama, Costa Rica, Columbia, Ecuador, and Brazil (Bigelow, 2001, Fleischbein et al., 2006, Nova et al., 2007, Kinner and Stallard, 2004). Despite the success of the Penman-Monteith method, SWAT was individually run with the three evapotranspiration models, prior to calibration procedures, in order to ensure that the Penman-Monteith method is indeed the most appropriate for use in the TCH basins. The resultant flow output from each run was statistically compared to observed daily values using linear regression analysis as an indicator of method appropriateness.

Similarly, SWAT provides two options for flow routing: the variable storage method (Williams, 1969) and the Muskingum method (Overton, 1966). Muskingum method is employed in areas where catchment storage significantly contributes to differences in discharge and is often used in flood prediction studies. The variable storage method was then chosen for SWAT simulation because catchment storage is not considered a significant effect in THC.

Runoff may be predicted using two methods. The SCS curve number (SCS, 1972) was chosen for runoff prediction rather than the Green-Ampt Mien-Larson method (Mien and Larson, 1973). The Green-Ampt method was not chosen because it requires sub-daily precipitation data which is not available for the TCH area.

Model Simulation

After the set-up procedure was completed, the SWAT model was run for a simulation period from January 1, 2004 to December 31, 2006 for the CQ basin.

4.3 Calibration and Validation

Model calibration and validation are two distinct, but related, procedures which are essential for ensuring and quantifying model accuracy. Calibration is the adjustment of model parameters to maximize the "goodness-of-fit" of model output with an observed dataset, while validation is the comparison of the calibrated model with an independent set of observed data and involves no further parameter adjustments. Data used for model calibration and validation should be distinct from each other but also be of adequate time length to represent a range of hydrologic conditions.

Streamflow and suspended sediment data for 2004 and 2005 from the CQ1 station were used for calibration and data from 2006 was used for validation. All data were adapted from daily streamflow and sediment records provided by the ACP (ACP, 2005b, ACP, 2006b, ACP, 2007). Although available, data from 2003 was excluded from calibration and validation procedures for two reasons. Firstly, precipitation records from the ZAN station, of closest proximity to CQ1, are incomplete for all of 2003, thus an accurate representation of streamflow at this site may not be generated by the model. Furthermore, 2003 emerged as an unusual hydrologic year in the Caribbean region due to an El Niño event. This increased seasonal temperatures and prompted a drier-than-average dry season and heavy rains during the wet season (Levinson and Waple, 2004). With the exception of precipitation, all climatic input data are estimated using the weather generator model and, because no temperature data is available for the TCH basins, weather variations, such as the El Niño anomalies, cannot be integrated into the model. Moreover, model calibration using data from years that significantly deviate from the average could result in unsuitable parameter modifications and would, consequently, compromise the model's ability to accurately simulate processes.

The Nash-Sutcliffe (E_{NS}) coefficient of model efficiency and the r-squared (r^2) coefficient of determination were both used as indicators of model performance for calibration and validation periods. Models with higher E_{NS} and r^2 coefficients are presumed to perform better than models with lower coefficients. The E_{NS} coefficient of efficiency is calculated using the following equation:

$$E_{NS} = 1 - \frac{\sum_i (P_i - O_i)^2}{\sum_i (O_i - \overline{O})^2}$$

The r^2 coefficient of determination is calculated using the following equation:

$$r^2 = \left(\frac{\sum_{i=1}^{n} (O_i - \overline{O})(P_i - \overline{P})}{\sqrt{\sum_{i=1}^{n} (O_i - \overline{O})^2} \sqrt{\sum_{i=1}^{n} (P_i - \overline{P})^2}} \right)^2$$

Where P_i is the predicted value O_i is the observed value at time i, $\bar{O}$ is the mean observed value, and $\overline{P}$ is the mean predicted value for the entire time period i.

According to Krause et al. (2005), using E_{NS} and r^2 to evaluate hydrological model performance has limitations due to their sensitivity to peak flows. This sensitivity, Krause et al. (2005) points out, is because parameter calculations are based on the square of the difference between the simulated and the observed values; therefore, these parameters are unreliable indicators of model performance for low flows. To account for this sensitivity, Krause et al. (2005) propose variations of E_{NS} and r^2 which are similar or superior indicators of model performance. The E_{NS} and r^2 coefficients were chosen for this study because they are recommended for use with SWAT (Neitsch et al., 2002). Using indicators of model performance that are consistent with current literature, such as E_{NS} and r^2, also facilitates model comparison. Nevertheless, the relative Nash-Sutcliffe (E_{rel}) coefficient, a less sensitive coefficient recommended by Krause and colleagues (Section

5.1), was calculated to validate the reliability of E_{NS} as a model performance indicator for this study

Calibration

The calibration procedure was performed in a step-wise fashion; model parameter input values were adjusted (decreased or increased) by a certain incremental value which varied for individual parameters according to their respective input range. The effect of these input alterations on observed streamflow and sediment from CQ1 was evaluated with the E_{NS} and r^2 coefficients. These were then compared with the coefficients derived from model output from the previous incremental change. If the E_{NS} and r^2 coefficients increased, the parameter value would again be altered by the same increment; if the value decreased, the parameter would be altered (decreased or increased) at a smaller incremental change (generally half of the previous increment). If the model efficiency was lower, the previous parameter value would be considered the final value, if not, the parameter would be again adjusted in the same incremental fashion. This step-wise procedure was iterated several times until optimal values were reached for both the E_{NS} and r^2 coefficients. The effects of parameter adjustments on flow were also visually examined by graphically comparing model output with observed data.

Model calibration was first performed with streamflow on a monthly and then a weekly time step. Model evaluation at a yearly time step, generally recommended as the calibration starting point, was not feasible due to the limited number of years of observed data (three) – too small a sample size to perform reliable statistical analyses. A weekly time step, as opposed to a daily time step, was chosen for two reasons. Precipitation records are not available at or around the stream gauge site (CQ1) used for calibration (Map 1, page 9); therefore, accurate model predictions for daily streamflow may not be possible without more spatially detailed precipitation input data. In fact, precipitation patterns at CQ1 may differ somewhat from the recorded precipitation data at ZAN or CCA, due to the isthmian rainfall gradient; the difference in recorded precipitation between stations can be seen in Figure 4. Therefore evaluation of model performance at a weekly time-step may eliminate some of the error associated with the aforementioned factors as well as error associated with generating daily average streamflow output from total (cumulative) daily precipitation input.

Following streamflow calibration, suspended sediment was calibrated and evaluated at a monthly time-step. This time-step was chosen because sediment model output is sensitive to land management practices, in particular tillage (Neitsch et al., 2002). Although the data available for the TCH basins is detailed (IDIAP, 2007, unpublished), information on the activities of each pineapple producer in the region is not available. More importantly, while the start and end dates of major land management activities is available, field rotations on large-scale plantations are not considered. Pineapple crop rotations are commonly practiced on plantations so as to have continual fruit harvest (see Appendix II). Considering the lack of such detail and model sensitivity to land-management, evaluation at a monthly time-step seems more appropriate to account for some of these discrepancies.

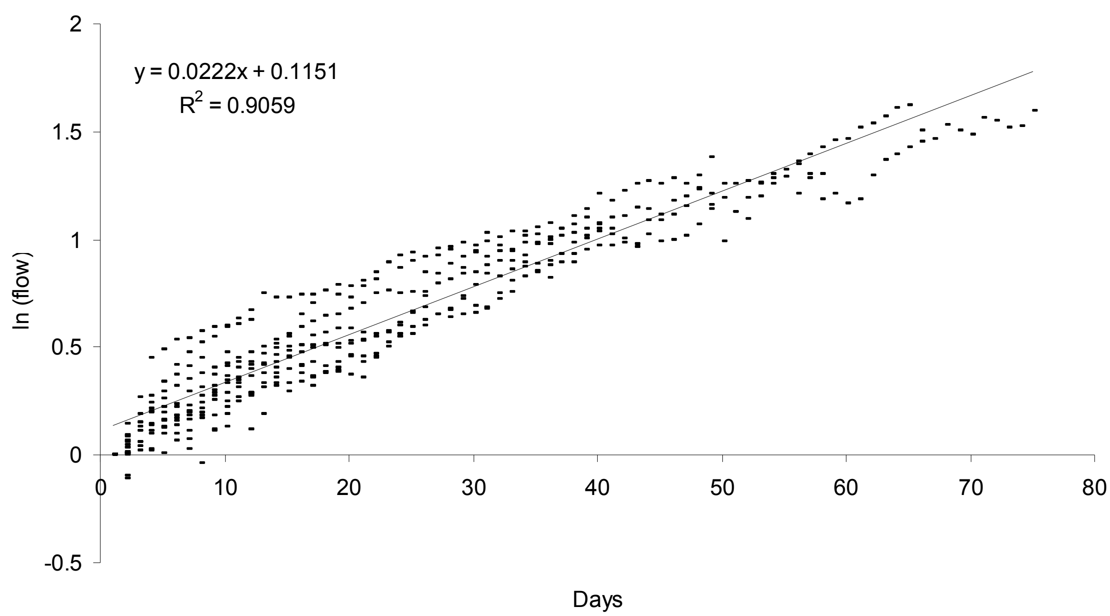


Figure 6: All recession periods greater than 10 days observed from 2003 to 2006 at CQ1, used to determine the groundwater recession coefficient. Points represent the natural logarithm of the average daily flow during the recession period.

All model parameters that were modified during the streamflow and sediment calibration procedures and their final values are shown in Appendix I, Table 5. Parameter definitions are outlined in Appendix I, Table 6. The value for the alpha base-flow factor was not determined through the step-wise calibration process; it was instead calculated using the master recession curve method (Figure 6). The value derived from this method was used as the input value for the alpha baseflow factor (Appendix I, Table 5).

Validation

Streamflow and suspended sediment observed at CQ1 in 2006 was used for SWAT model validation. Validation procedures were performed independently of the calibration procedure. The model performance during the validation period was evaluated using the E_{NS} and r^2 coefficients.

Sensitivity Analysis and Model Uncertainty

Calibration procedures involve the estimation of, sometimes numerous, model parameters; modelers cannot, therefore, be certain if chosen parameters and their estimated values adequately represent a system without ground-truth data from which to evaluate or derive model parameters. Modelers can, however, examine and quantify the effects of changes in input parameter values on output through a sensitivity analysis. Via such an analysis, model uncertainty may be ascertained, an estimate of the amount by which an observed or calculated value may depart from the true value.

Beyond the estimation of calculated or measured model input parameters, uncertainty is also a function of the measurement errors, heterogeneity, and grid-cell resolution associated with spatial input such as DEMs and land-use/land-cover and soil maps. The sensitivity of the model to these inputs, however, is somewhat more difficult to quantify without multiple DEMs or maps of varying resolution with which to compare their effects on model output. This study does not attempt to analyze the sensitivity of the SWAT model to these inputs.

To examine the sensitivity and quantify the uncertainty of SWAT model input parameters, a computational approach using the Morris screening procedure (Morris, 1991, Campolongo et al., 2003) was taken. The Morris method may be used as a means to distill the overall number of variables in distributed models to a set of key parameters which significantly impact model performance. The Morris method is based on a one factor at a time design, in which a random set of model input parameters is chosen and the values of each parameter is modified by a sampling step (Δ) between successive model runs. Morris (1991) and Campolongo et al. (2003) propose two sensitivity measures: the absolute mean (μ^*) and the variance (σ) of the elementary effect (e_i) of a given model parameter, *i*. The absolute mean can be used to gauge the importance of model inputs on model outputs while the variance can illuminate parameter-parameter interactions or parameters which have non-linear effects on output. The elementary effect measures the change induced by parameter modification and is calculated using the following equation:

$$e_i = \frac{y^* - y}{\Delta_i}$$

Where y^* is the new model outcome, y is the outcome from the previous model run, and Δ_i is the variation in parameter *i*.

To fully identify model sensitivity to a given parameter, a set of samples must be taken to adequately represent the input parameter distribution (F_i). For the sensitivity analysis performed in this study, the sampling step (Δ_i) was generally fixed to 25% intervals for each parameter range, resulting in four samples from the input parameter distribution, in accordance with recommendations made by Morris (1991). In order to reduce the computational demands of the Morris procedure, it was decided to implement a stratified sampling of input parameters. Parameters considered in this procedure are sixteen parameters commonly modified during calibration procedures, identified through the current SWAT literature, and five additional parameters related to the soil input data (Appendix I, Table 6). The Morris sensitivity analysis was performed using the SIMLAB interface (Saltelli et al., 2004) and streamflow and sediment model output was compared.

Following the Morris procedure, the uncertainty of some of the most sensitive parameters identified in the SWAT literature and in this study was quantified (CN, GWQMN, RCHRDP, BD, AWC, and Ksat - see Appendix I, Table 5 and Table 6). These parameters were adjusted by ±10% from their final value determined during calibration procedures (Appendix I, Table 5) and the changes in the E_{NS} coefficient were graphically compared.

Additional Stochastic Methods

Complementary statistical methods were also employed to provide more insight into SWAT model performance. The Cook's Distance (Cook, 1977), a method used to identify data outliers and quantify their influence on the regression model, was calculated for all datasets. Given the small sample size of the observed data, targeting and eliminating extreme variations from the norm (e.g. if a 100 year storm is represented in the dataset or a prolonged drought) can facilitate model calibration and boost model accuracy.

The observed and simulated cumulative water and sediment yield at CQ1 were examined using the Kolmogorov-Smirnov test (KS) and Mann-Whitney test (MW). These are non-parametric methods used to test the similarity of sample distributions. The KS method generates a D-statistic, representing the maximal distance between cumulative frequency distributions of two samples. The MW ranks the difference between means of the two samples, yielding the U-statistic. As a general rule, the U-statistic will approach the Z-score for large sample sizes ($n \geq 40$). These tests were performed using the SPSS® interface.

5.0 Results

The SWAT model was calibrated with data from 2004 and 2005 and validated with data from 2006 for streamflow and transported sediment at the CQ1 gauge (Map 1, page 9). Initial runs of the uncalibrated SWAT model showed a tendency to over-predict flow. Although adjustments of flow parameters such as CN values and parameters related to surface lag and flow time (Appendix I, Table 5) did improve flow prediction accuracy, simulated values remained consistently high. Groundwater and evapotranspiration parameters (Appendix I, Table 5) were then adjusted, enhancing model performance for streamflow but leaving baseflow predictions with considerable error. The subsequent sediment calibration, on the other hand, proved to be an onerous process. SWAT consistently over-simulated suspended sediment for the 2004 calibration year and under-simulated for 2005. Consequently, model performance remained poor despite considerable parameter modifications. To elucidate some of the reasons behind these observations, the following section presents streamflow and sediment calibration and validation, highlights key model components and processes, and discusses spatial and temporal accuracy apropos the SWAT application in the context of the TCH basins and the greater PCW.

5.1 Flow Calibration and Validation

Overall, the SWAT model is able to simulate streamflow and baseflow at the CQ1 gauge very well, with notably better model performance for the validation periods (Figure 7 and Figure 8). The minor disparity of model performance for the validation and calibration periods of both streamflow and baseflow may be in part justified by the coefficients selected for model evaluation (E_{NS} and r^2) which, according to Krause et al. (2005), are sensitive to peakflows. The difference between observed and predicted values (factors in the E_{NS} coefficient numerator) is largest in mid-wet season months when precipitation is intense and peakflows are at their height (Figure 9 & Figure 10); thus the calibration period, having a larger sample size, will contain more error than the validation period. The difference in model performance for baseflow calibration and validation periods (E_{NS}

difference = 0.1) is about five times that for streamflow (E_{NS} difference = 0.02). Overall, peakflows tend to be over-predicted more so for baseflow than for streamflow predictions (Figure 10). Based on this evidence, we can postulate that if the coefficient is very sensitive, the validation period may in fact show better performance due to the chosen evaluation coefficients.

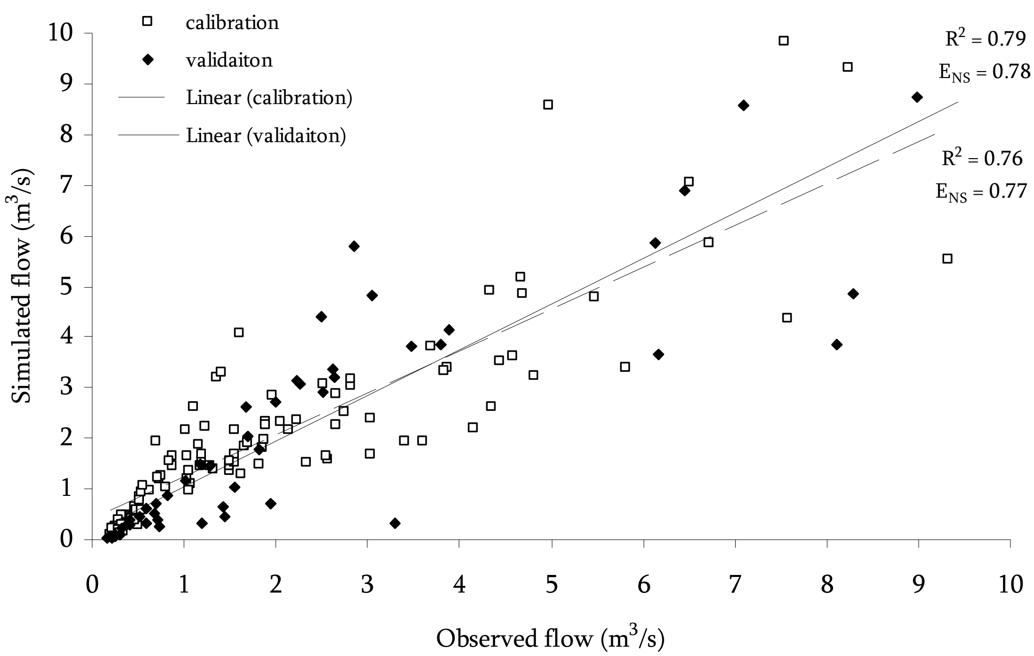


Figure 7: Weekly average streamflow for calibration and validation periods.

In their study, Krause et al. (2005) determined that E_{rel} coefficient[4], a modified version of the E_{NS} coefficient, is less sensitive to peakflows. Calculation of the E_{rel} with calibrated model output yields E_{rel} values of 0.72 and 0.79 for streamflow calibration and validation periods, respectively, and 0.62 and 0.70 for baseflow calibration and validation periods. Although model evaluation with the E_{rel} coefficient indicates inferior model performance,

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[4] The E_{rel} is calculated with the equation below; where O_i is the observed value and P_i is the predicted value at time i, and $\overline{O}$ is the mean observed value for the time-step.

$$E_{rel} = 1 - \frac{\sum_{i=1}^{n} \left(\frac{O_i - P_i}{O_i} \right)^2}{\sum_{i=1}^{n} \left(\frac{O_i - \overline{O}}{\overline{O}} \right)^2}$$

it nonetheless signifies a respectable model, thereby confirming the validity of E_{NS} coefficient for use in this study. Unlike the E_{NS} coefficient, however, the difference between E_{rel} values for calibration and validation periods of both streamflow and baseflow are comparable (difference for both ~ 0.08), presumably owing to the sensitivity issue. In sum, evaluation with both the E_{rel} and E_{NS} coefficients reinforces the superior prediction of flow for the validation period and demonstrates that the chosen evaluation parameters are not likely responsible for the calibration-validation difference but, instead, may be due to chance given the small sample size.

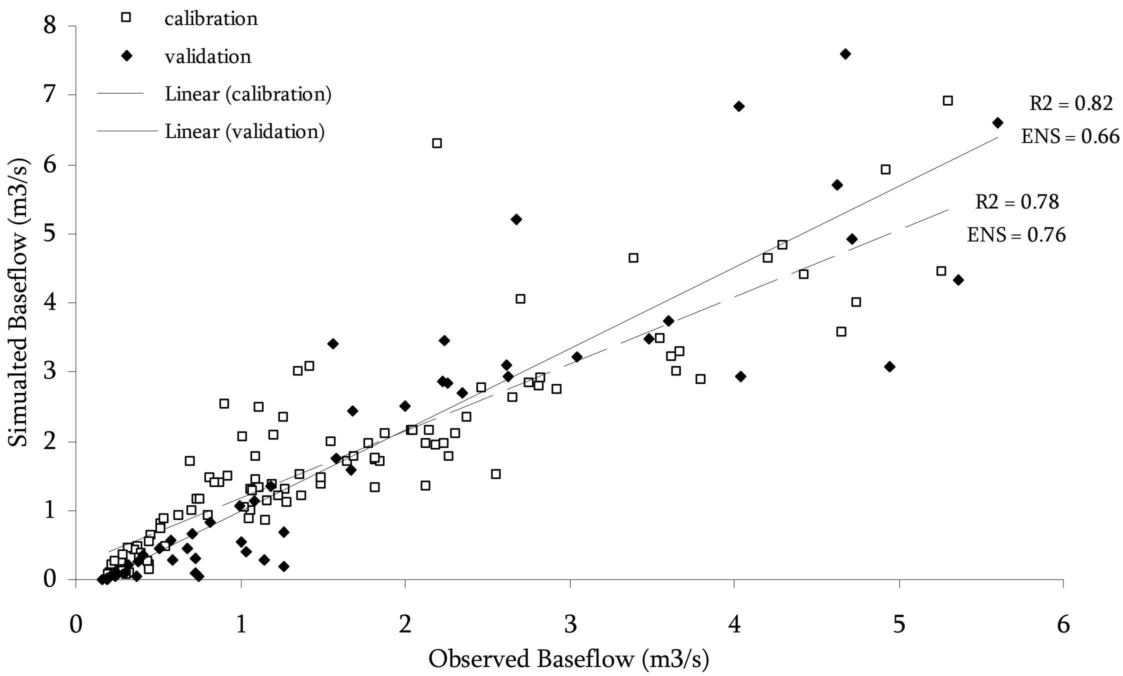

Figure 8: Weekly average baseflow for calibration and validation periods.

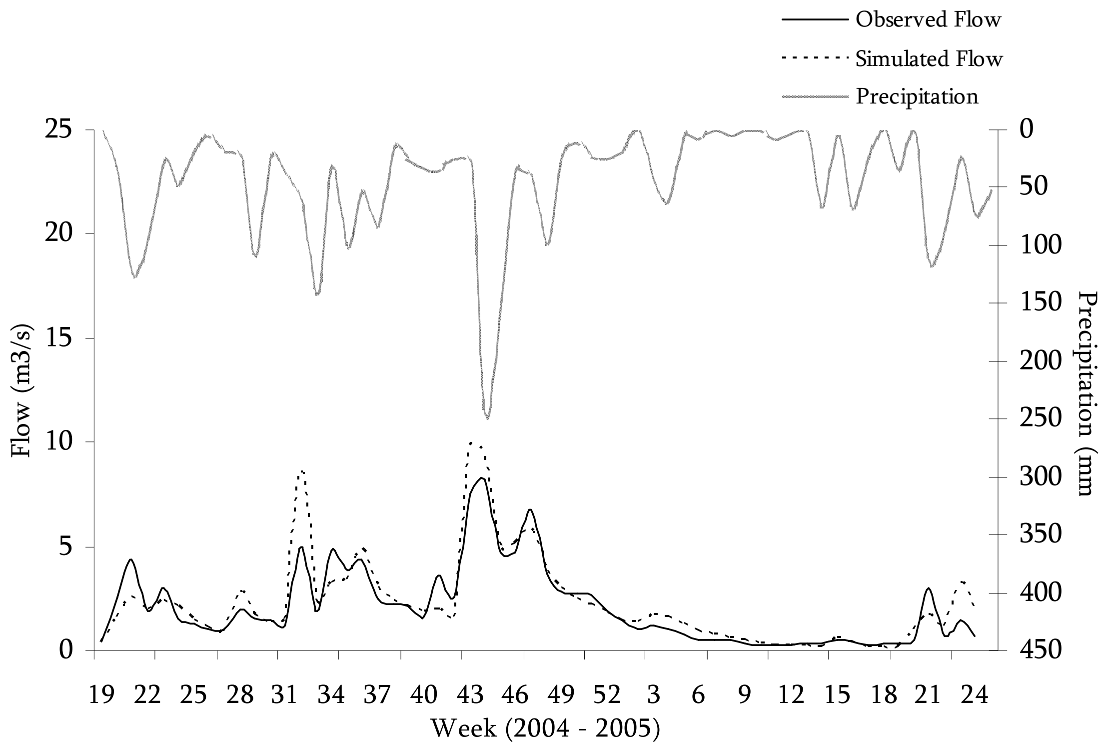

Figure 9: Example of weekly average flow at CQ1 for calibration period, exhibits that the model simulates recharge and baseflow decline well, while peak flow is often over estimated. Precipitation also shows that the model is more responsive to heavy precipitation that the real watershed and appears to produce instantaneous runoff more quickly.

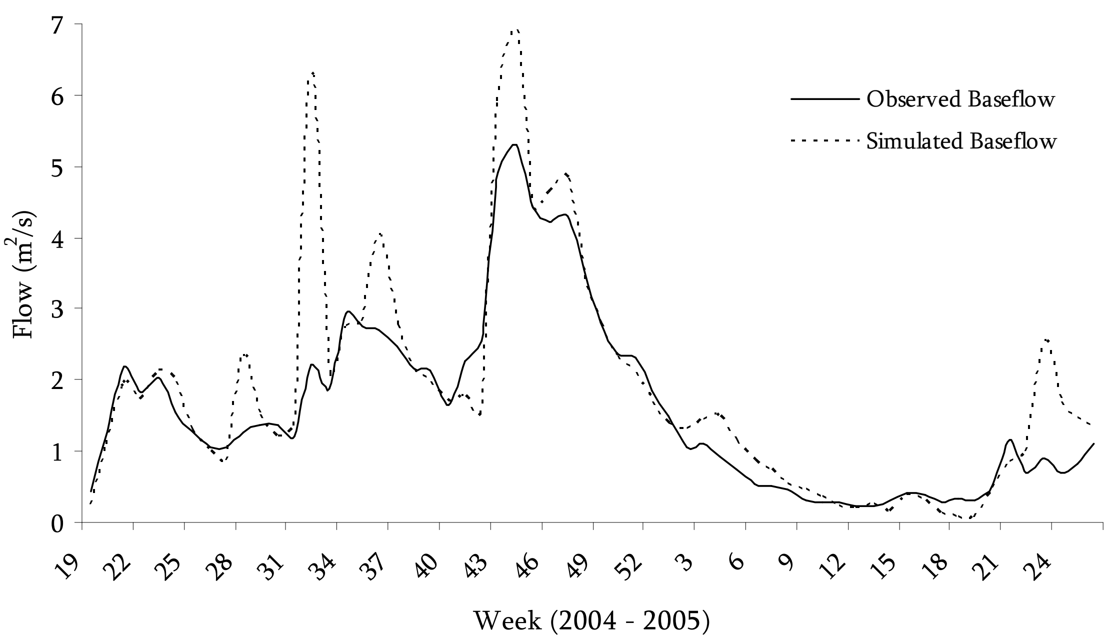

Figure 10: Weekly observed and simulated baseflow at CQ1 for calibration period.

The standardized residuals for streamflow are near randomly distributed, perhaps with a slight downward trend with increasing flow (Figure 11). There is little significant error for streamflow; in fact, the only prominent outlier is that produced for the extreme precipitation event in October 2004 (Figure 9, Week 44). Conversely, baseflow residuals show a more pronounced trend of under-prediction for lowflow periods and over-prediction for highflow periods (Figure 12). Comparatively more baseflow predictions are significantly different (outside the 95% confidence interval) than for streamflow, suggesting that some of the error associated with baseflow predictions is not due to chance alone. While uncertainty associated with soil hydraulic properties and groundwater modeling components could indeed be contributing factors (discussed in section 5.6), the spatial representativeness of precipitation records used for model input may also be a source of model error. As shown in Figure 4 (Methods section), precipitation in other areas of close proximity to the ZAN station differs in both events and amounts. This station may not, therefore, provide sufficient spatial detail to characterize precipitation patterns across the entire area which would account for some discrepancy in the observed and simulated flow.

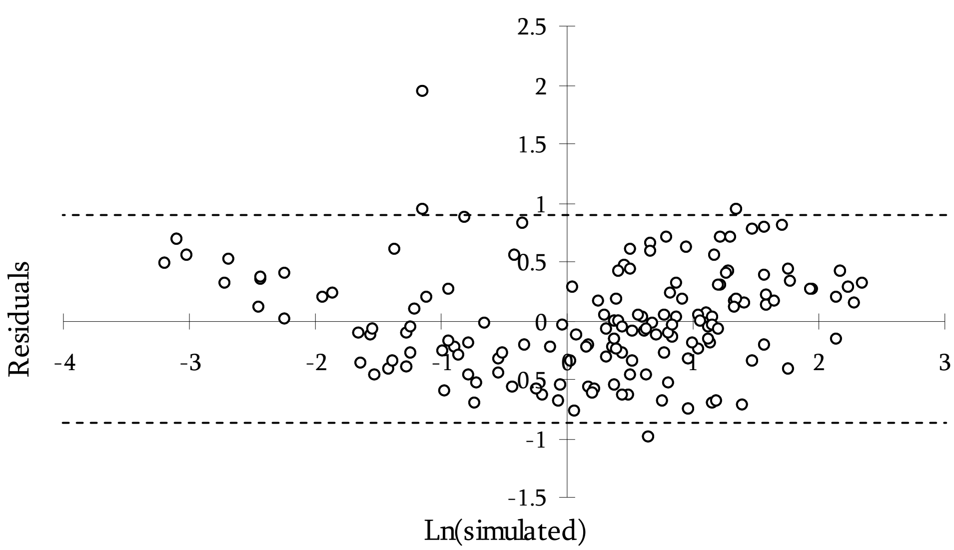

Figure 11: Average weekly standardized residuals for streamflow predictions of the calibration and validation periods with 95% confidence interval.

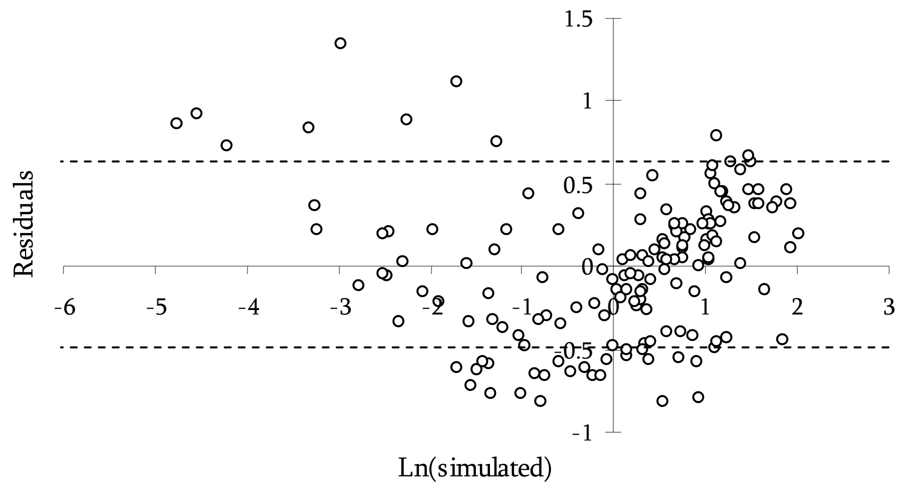

Figure 12: Average weekly standardized residuals for baseflow predictions of the calibration and validation periods with 95% confidence interval.

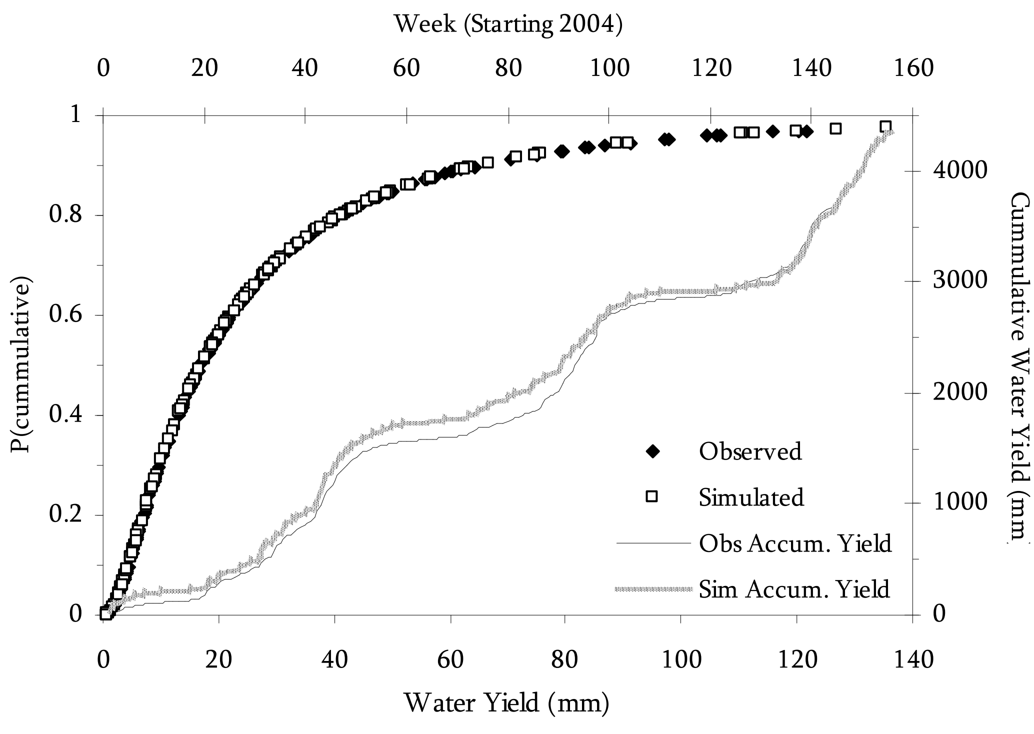

Figure 13: Comparison of the cumulative probability density functions of the log-normal distribution for monthly simulated and observed water yield (primary axes) and the total simulated and observed water yield accumulated at CQ1 for the calibration and validation periods (secondary axes).

A comparison of the cumulative probability distributions of simulated and estimated weekly water yield (Figure 13) illustrates that the probability of SWAT generating a value for water yield that is statistically different from the observed value is very low.

This is similarity reflected in the results of the Kolmogorov-Smirnov (KS) and Mann-Whitney (MW) tests, which confirm that the distributions of the simulated and observed cumulative water yield do not significantly differ (Table 2).

Table 2: Results of the Kolmogorov-Smirnov (KS) and Mann-Whitney (MW) tests for cumulative water and sediment yields.

	Cumulative Water Yield	Cumulative Sediment Yield
Z Score (MW)	1.083*	0.304*
P value (MW)	0.079	0.276
D statistic (KS)	0.122*	0.278*
P value (KS)	0.032	0.082

* Significant at a $\alpha = 0.05$

5.2 Sediment Calibration and Validation

Despite the generally accurate flow predictions, SWAT is not a good predictor of monthly sediment yield in the CQ basin (Figure 14 & Figure 15). Because model performance at the monthly time-step is poor, model evaluation at the weekly level was considered ineffectual. More to the point, weekly sediment yields are not of particular importance in the context of the PCW where reservoir sedimentation is the principal concern; therefore, monthly or annual sediment yield simulations should be sufficient for watershed management planning or decision making.

Mirroring streamflow predictions, model performance is poorest during the calibration period (Figure 15), yet the calibration-validation coefficient discrepancy is notably larger. Excluding the sensitivity of the E_{NS} coefficient, improvement beyond this performance level for the calibration period was unattainable because the model consistently over-simulated suspended sediment in the year 2004 and under-simulated in 2005 (Figure 14). Since calibration years were evaluated together, parameter adjustments during calibration procedures would bring about the simultaneous improvement of model performance for one year and the decline in model performance of the alternate year, resulting in no considerable improvement overall. Although the marked land-use transition in the CQ basin (Map 2a, page 10) was accounted for in model calibration procedures (see Section 4.2), the diametric difference in prediction patterns is likely largely influenced by the uncertainty associated with the erosion parameter inputs, as discussed below, and caveats linked to modeling pineapple land cover (see Appendix II for an evaluation and discussion).

The Cook's Distance analysis, used to explore the inconsistency between simulated sediment in 2004 and 2005, identified sediment yield simulated for the month of October, 2004 as an outlier with heavy influence on the regression model. Given that the calibration period data set is small and that an extreme precipitation event occurred in October of 2004 (Figure 9, week 44), it was decided that this data point should be excluded from further model performance evaluations [5] (E_{NS} and r^2 calculations). Following additional parameter adjustments, performance improved for both the calibration and validation periods, suggesting that the inclusion of the outlier in coefficient calculations could result in erroneous modification and thus substantiates the decision to exclude it.

The standardized residuals of the sediment data appear to be non-random, demonstrating that much of the significant model error occurs for mid-range sediment predictions (Figure 16). Under high infiltration conditions, as mathematically proven by Kinnell and Risse (1998), MUSLE tends to (increasingly) overestimate low values of soil loss. While attributing some of the model error to the inappropriateness of MUSLE for erosion prediction is justifiable (Kinnell, 2005), this proven tendency to overestimate illuminates a possible reason why significant error is exhibited principally during the periods of seasonal transition, when sediment yield is in the mid-range (Figure 16). Another possible source is the SCS-CN method – used for MUSLE runoff factor calculations – whose accuracy is reduced when surface runoff is less than 13 mm (Rawls et al. 1986).

[5] Although model error for streamflow and baseflow was significant for the October 2004 event (see Figures 10 to 13), the influence of this data point on the regression model in these cases was likely not heavy given the larger calibration sample size (at the weekly time-step).

This is observed for smaller events in CQ such as those occurring during the dry season and seasonal transitions when sediment loadings are in the low to mid-range. Because the MUSLE runoff factor represents the energy used for particle detachment and transport (See Section 2 for details), the SCS-CN method could be one factor contributing to sediment yield under-predictions.

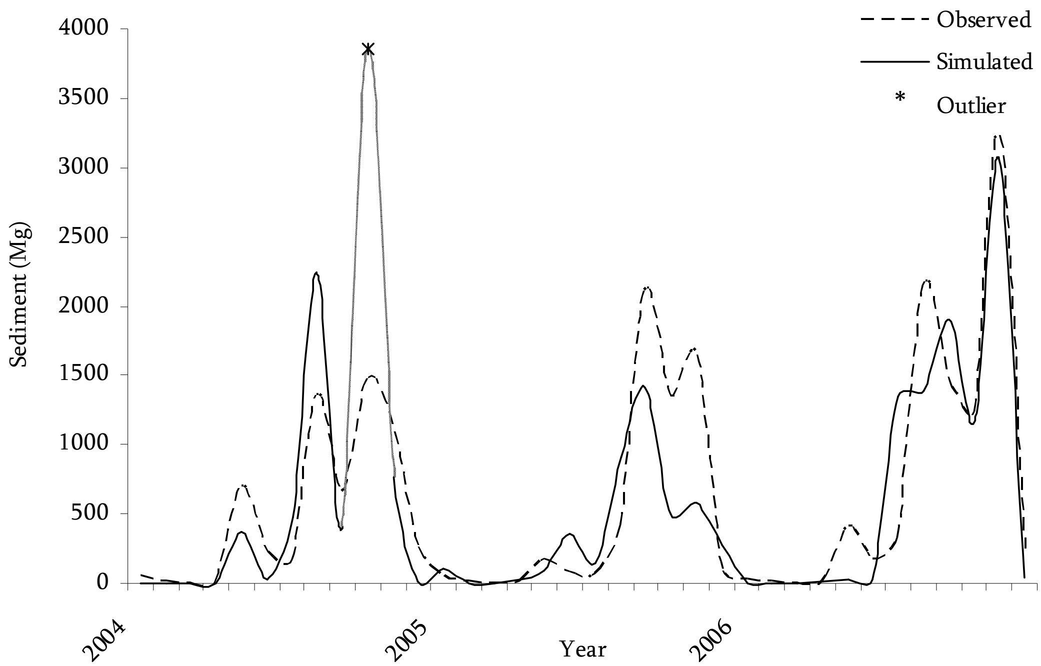

Figure 14: Monthly observed and simulated sediment yield and flow at CQ1 for calibration and validation periods.

Beyond suspended sediment at CQ1, there is no empirical data with which to compare simulated erosion rates in the basin; a comparison with results of other erosion estimates in the CQ basin, however, demonstrates startling differences. The average annual erosion predicted by SWAT is 2.5 Mg/ha/yr, an exceptionally low estimate when compared to the RUSLE-derived estimate forecasted by I&N (1996), predicting annual erosion to be 29 Mg/ha/yr and sediment yield[6] to be 58826 m^3/yr. These alarmist estimates were calculated before monitoring began in the basin which now shows that actual annual sediment yield is nearly 7 times less (~4 Mg/ha/yr), on average[6] 8535 m^3/yr (ACP, 2005a). The USLE factors of the I&N study were assumed to be uniform across the basin and the model was not calibrated for the region, thus likely paramount sources of these

[6] Using a density of 1.2 m^3/Mg as calculated by I&N.

unrealistic predictions. The USLE and RUSLE models also fail to explicitly consider the effects of runoff and results in a tendency to over-predict erosion (Kinnell, 2003, Kinnell, 2005). This is certainly corroborated by a comparison of the MUSLE-derived and USLE-derived estimates from the SWAT model output, which demonstrates that USLE over-predicts erosion for both pasture and pineapple land-cover.

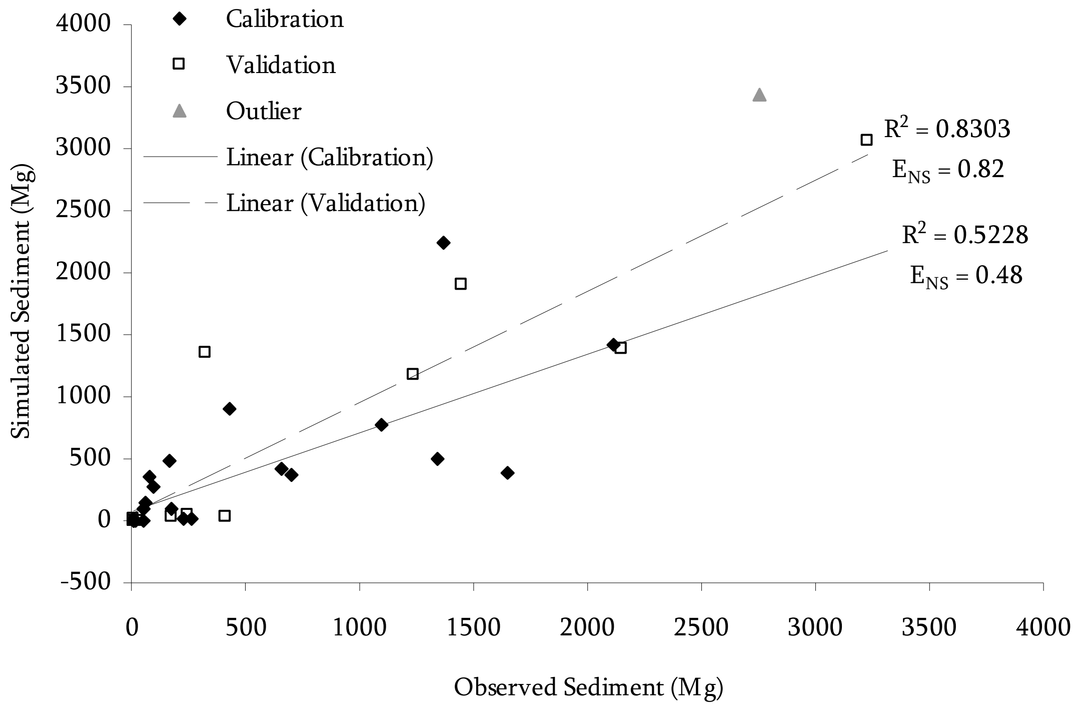

Figure 15: Monthly total sediment yield observed and simulated at CQ1 for calibration and validation periods. The outlier, identified using Cook's Distance method, was excluded from model coefficient calculations.

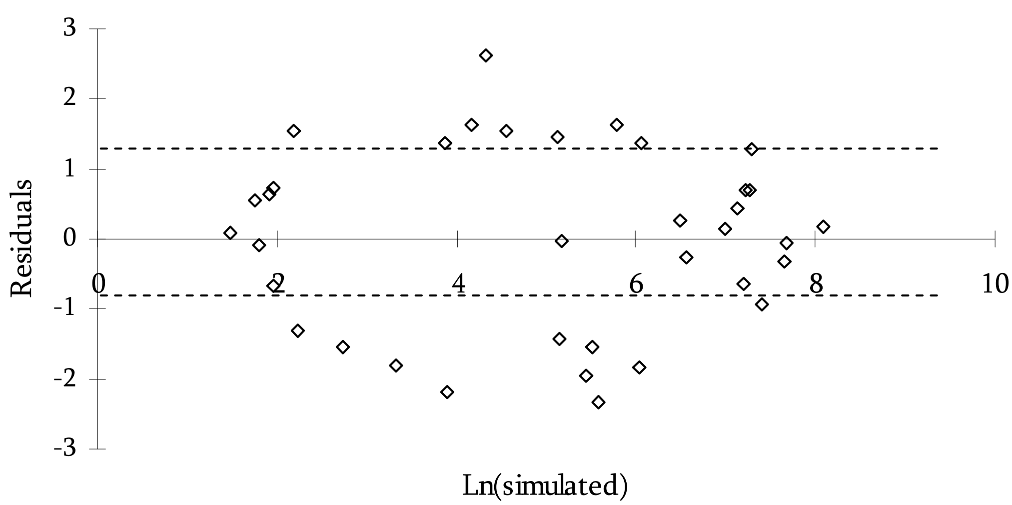

Figure 16: Standardized residuals for sediment predictions with 95% confidence interval. The October 2004 outlier is excluded.

Regardless of the poor model performance at the monthly time-step (Figure 14, Figure 15 & Figure 16), the model does appear to be a moderately good predictor of cumulative sediment yield over the three year observation period (Figure 17). The cumulative probability of the simulated and observed monthly sediment yields demonstrates that there is about a 12% probability that the model will produce a prediction significantly different from the observed value at low to mid-range values (Figure 17). As the monthly sediment yield increases, the probability that model predictions will be different from observed values decreases (as the probability density functions converge). This indicates that the overall probability of the model adequately predicting accumulated sediment over the entire year is likely. In fact, for sediment yield predictions beyond 1000 Mg/month or more there is very little probability that the model will be a poor predictor; this is similarly reflected in the results of the MW and KS tests (Table 2, page 59).

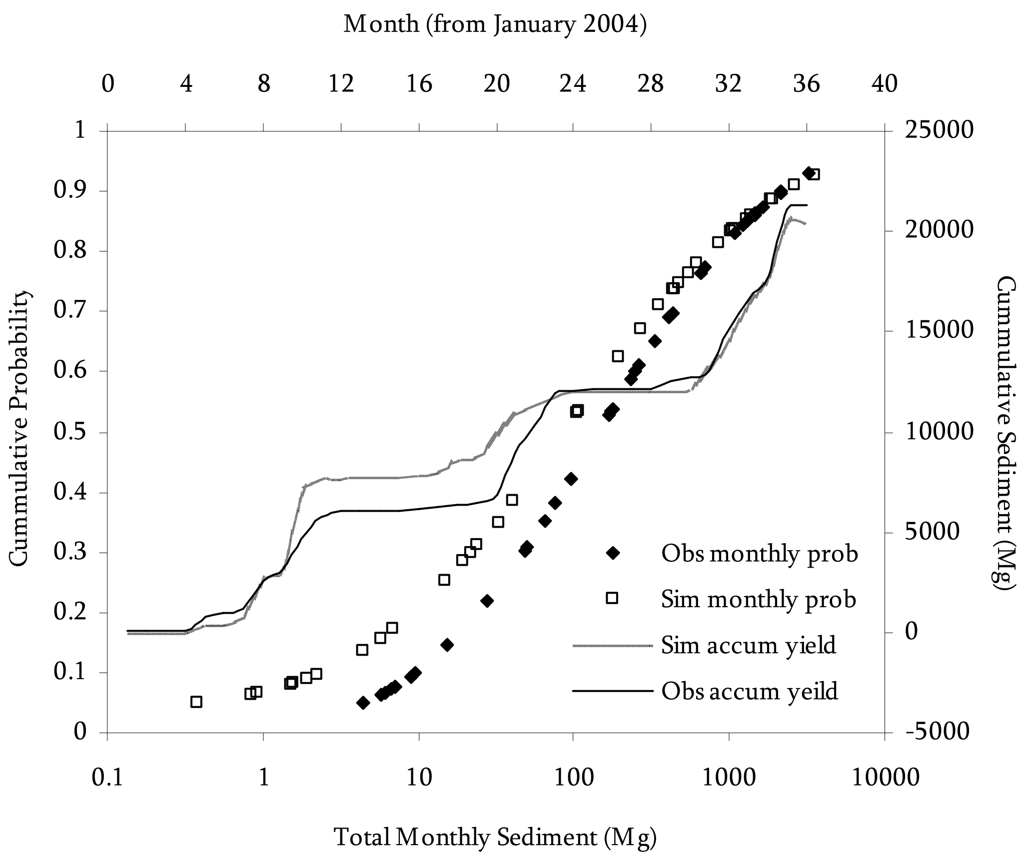

Figure 17: Comparison of the cumulative probability density functions of the log-normal distribution for monthly simulated and observed sediment yield (primary axes) and the total simulated and observed sediment yield accumulated at CQ1 for the calibration and validation periods (secondary axes)

5.3 Water Balance

The average annual simulated water balance for the CQ basin is shown in Figure 18. The surface runoff and baseflow components were reasonably simulated by SWAT and will not be discussed in further detail here. Instead simulated evapotranspiration (ET) and groundwater recharge are examined. In view of the consistent flow over-predictions in the pre-calibrated model, it is important to consider the accuracy of simulated ET – which is a factor determining the amount of precipitation that will become surface or subsurface flow – and groundwater prediction. Data available for CQ basin is such that only streamflow and sediment can be qualitatively analyzed; consequently, this discussion is done in a qualitative and comparative manner.

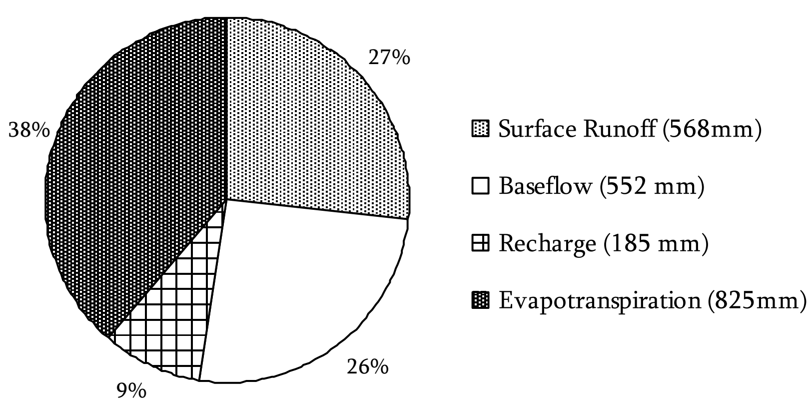

Figure 18: The percent contributed by various components of the annual average water balance for both calibration and validation periods over the entire subbasin.

The Penman-Monteith method, having the highest correlation with observed data (Figure 19), was chosen for successive SWAT model simulations. The average monthly simulated PET is shown in Figure 20, which corresponds to an average annual total PET of 998mm. Wang and Georgakakos (2007) calculated PET across the PCW using the Penman-Monteith method, estimating slightly higher values for the TCH subbasin, ranging between 1000-1200mm/year (Wang and Georgakakos, 2007). The authors note, however, that there is a substantial amount of error associated with their analysis (±12%) attributed to the poor distribution of weather stations in the PCW. Although Wang and Georgakakos (2007) used data from the same weather stations as those employed in this study, their calculations involved first the interpolation of climatic data across the PCW, followed by PET calculations. SWAT, conversely, does not use interpolation techniques and instead calculates PET based on data from the weather station in closest proximity to a given subbasin. Gamboa station has a slightly lower overall evapotranspiration when compared to Balboa (Figure 20), conceivably due to the isthmian rainfall gradient which produces more annual cloud cover in Gamboa. Because Gamboa is in closer proximity to the CQ basin than Balboa, it is possible then that the lack of interpolation may contribute to the slightly lower PET values calculated by SWAT when compared to the results of Wang and Georgakakos (2007).

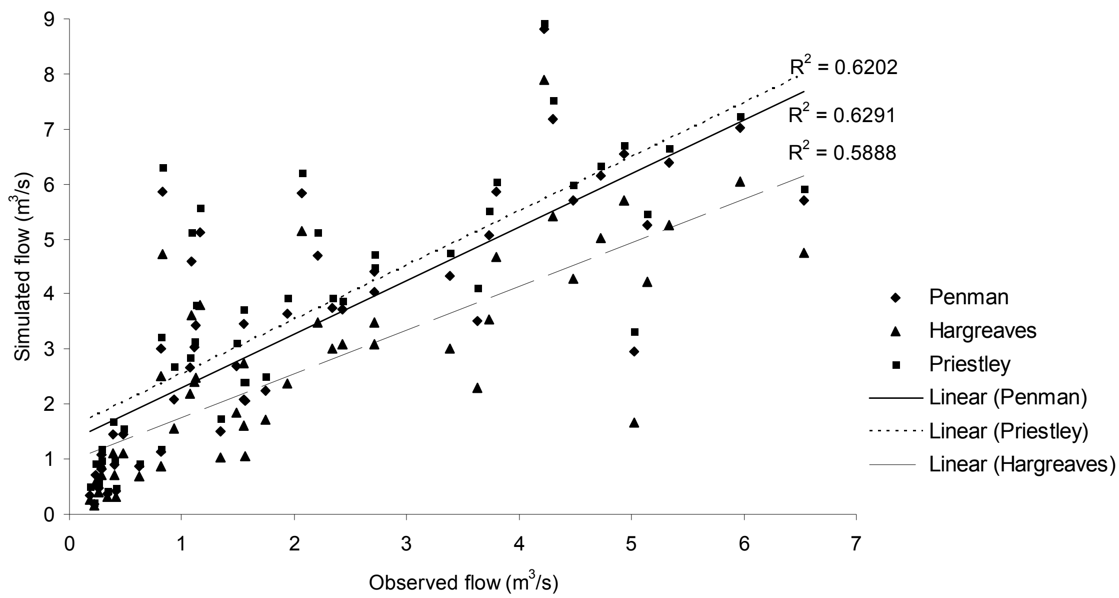

Figure 19: Observed and simulated flow using the three evapotranspiration models used in SWAT, the Penman-Monteith method (Penman), the Hargreaves method, and the Priestley-Taylor method (Priestley). The regression line for each model and the corresponding r2 value are shown.

Using satellite imagery, Hendrickx et al. (2005) analyzed actual ET for the greater PCW. According to their study, estimated ET in and around the TCH basins ranges from 1-

4mm/day (Hendrickx et al., 2005). The consistent over-prediction of average daily actual ET and flow during calibration procedures was remedied by increasing maximum canopy storage of pineapple, pasture, and forest cover as well as factors affecting soil evaporation (Appendix I, Table 5). SWAT was then able to consistently simulate average daily ET within the range given by Hendrickx et al. (2005). The basin wide daily average is predicted to be 2.3 mm/day (see Appendix II, Figure 31 for example).

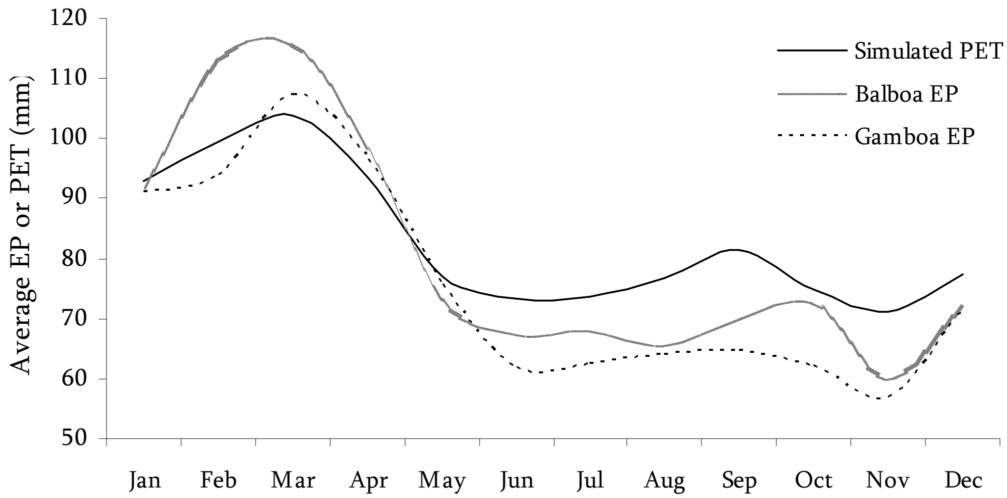

Figure 20: Average monthly PET simulated by SWAT and monthly average Class A Pan evaporation (EP) measured at Balboa (BAL) and Gamboa (GAM) Stations for years 2004 – 2006.

Aquifer recharge makes up the smallest portion of the water balance (Figure 18). Considering that the TCH basins are part of a larger system of underlying shallow aquifers which extends west and south of the study area (MICI, 1991), it is probable that water is transported in or out of TCH. As such, water leaving the physical system, which the modeled system does not account for[7], could be a source of the over-estimation of flow during calibration procedures and the substantial baseflow error. Groundwater parameters were adjusted to increase seepage into the deep underlying aquifers (Appendix I, Table 5), improving both baseflow and streamflow predictions and bringing water yields into a reasonable range. Because SWAT considers water entering the deep

[7] The SWAT delineated basin is modeled as a closed system, so groundwater entering or leaving the basin via the shallow aquifer is not considered.

aquifer as a loss to the system[8] (Arnold et al., 1993) (i.e. it cannot contribute to surface runoff, baseflow, or lateral flow) predicted values improved.

Without more information, it is difficult to assess the applicability of the groundwater parameter adjustments or to find evidence to support the assumption that water is transported out of the basin via groundwater systems. The AED (2004a) pump tests demonstrate that the deep underlying aquifers have very low permeability ($k = 7x10^{-04}$ - $7x10^{-05}$) and low storage capacity, suggesting that it is unlikely that water rapidly enters or refills these aquifers. Based on this evidence, the parameter modifications made may not be an accurate representation of the physical processes occurring in the system but, instead, a necessity to compensate for the groundwater flowing out of the basin via the superficial aquifer system. Indeed, the unjustifiable parameter modifications needed to improve flow predictions suggest, in accordance with Chu and Shirmohammadi (2000), that a foremost weakness of SWAT is its inability to model groundwater systems beyond delineated basin boundaries.

5.4 Soils

This section examines the components of the water cycle and sediment generation in relation to soil types. Because both soil hydraulic properties and soil erodibility were estimated exclusively based on texture, soils have been divided into groupings according to clay content to facilitate discussion and visualization (Figure 21).

Soil texture in the CQ basin is relatively invariable, dominated by clays and clay-loams classes of the USGS system. Figure 21 shows that almost all soils have between 41%-55% clay content (groupings C, D, and E) while groupings A, B and F account for just over 2% of soils in the area. Because the range of soil textures is narrow, the hydrologic parameters derived from PTFs, such as K_{sat} (Saturated hydraulic conductivity), BD (Bulk

[8] Actually, water can be released from the deep aquifer via evaporation if groundwater parameters are appropriately adjusted; otherwise it is assumed that this water contributes to flow outside of the delineated basin.

Density), and AWC (Available Water Capacity), and the K factor (soil erosivity factor) are relatively similar across all soil groupings in the area.

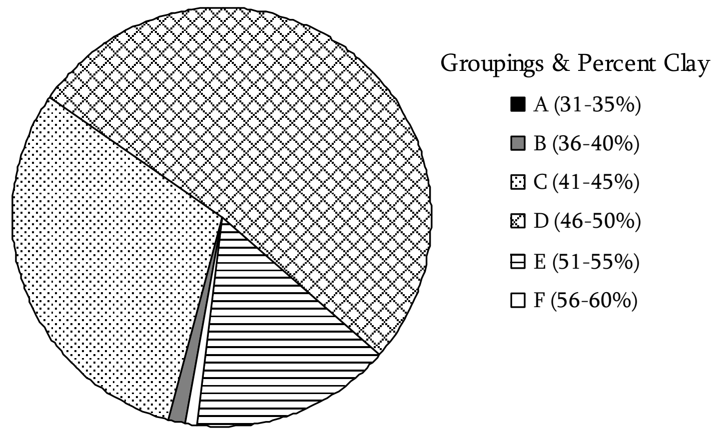

Figure 21: Percent area of soils in the CQ basin. Soils are divided into groupings according to clay content, by percent weight. Please also see Map 3, page 41.

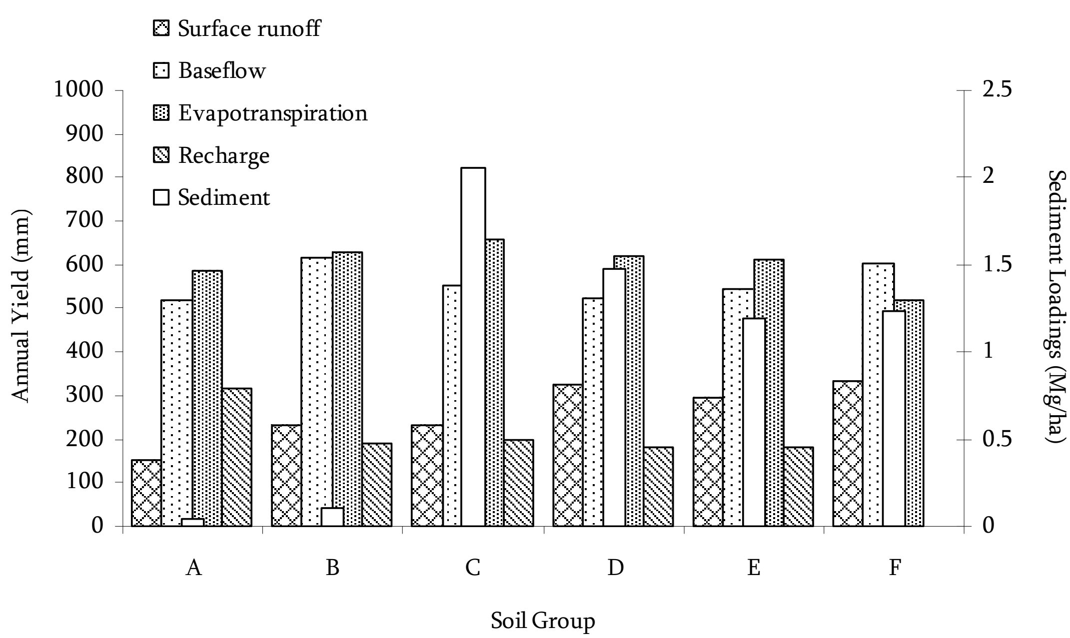

Figure 22: Average annual yield of the various components of the water balance according to clay content of soils.

The general invariability of soils in the CQ basin probably accounts for the lack of any visually discernable patterns in the hydrologic reactions of different clay groupings (Figure 22); there are, however, some notable differences. For example, recharge is non-existent within grouping F (suggesting that these soils may be at higher elevations), while other water balance components, such as baseflow and ET, occur at consistent levels throughout all groupings. Similarly, sediment yield for clay groupings A and B is low when compared to all other groupings.

5.5 Land-Use/Land-Cover

It seems unlikely, considering the aforementioned similarities in soil texture, that the variations noted in Figure 22 are attributed primarily to differences in soil properties. Examination of the land-cover over each soil grouping affirms this supposition (Figure 23). For instance, the only land-cover for soil grouping F, where no recharge is exhibited (Figure 22), is classified as urban (Figure 23). As surmised, this land-cover contributes minimally to recharge, a pattern consistent throughout all soil groupings (Figure 24). This is likewise echoed in sediment generation. Land-cover for clay groupings A and B, where relatively little sediment is produced (Figure 22), is principally forest or pasture (Figure 23). Figure 24 further illustrates this point, showing that the variation of water balance components and sediment generation across soils is largely a factor of land-cover.

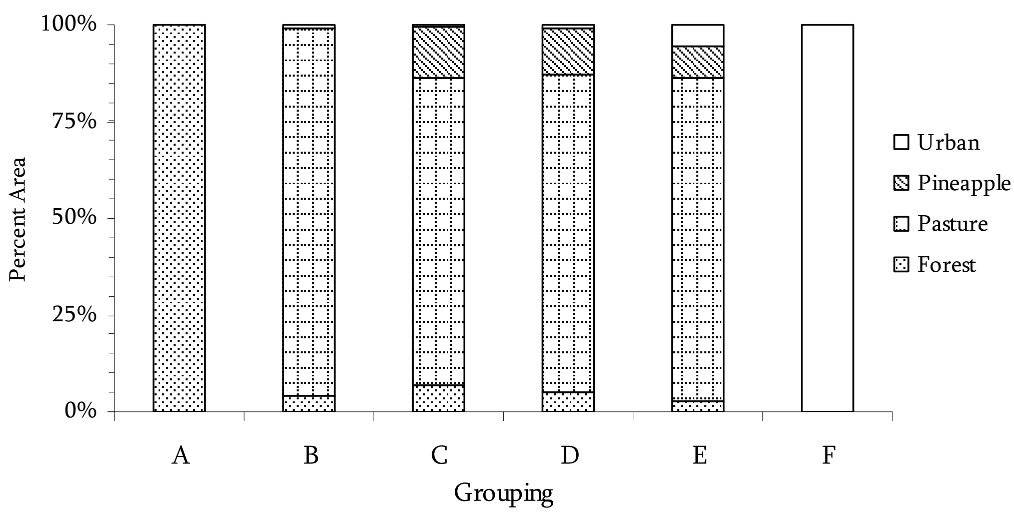

Figure 23: Percent area of land-cover for clay groupings.

SWAT simulates sediment loadings from pasture, the principle land-cover in the CQ basin, to be about 5% of total basin loadings (Figure 24). Principally used for livestock grazing, most range lands in the area have unsustainable carrying capacities and are considered to be overgrazed (Martiz and Vergara, 2004, AED, 2004b). Taking into account that SWAT cannot model the erosive effects of cattle grazing and hoof trampling, pasture may contribute to erosion in the CQ basin more than SWAT simulations indicate. On the other hand, the largest portion of sediment loadings is from pineapple cover (Figure 24). Without more quantitative data from the area, assessing the accuracy of simulated sediment loads from different land-covers cannot be assumed. Acquiring such data would most certainly allow fine tuning of the model and as a result improve basin-wide sediment yield simulations.

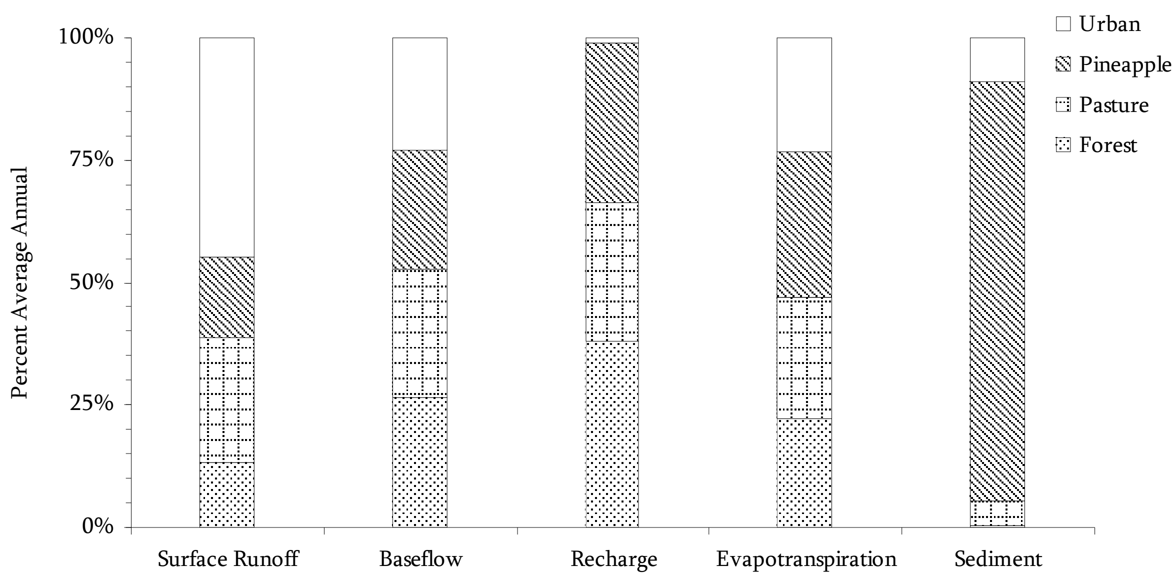

Figure 24: The portion contributed to the total annual yields by different land-cover.

5.6 Sensitivity Analysis

In addition to highlighting the results of the Morris sensitivity analysis, this section also sequentially discusses the uncertainty associated with the principal components of three parameter groupings: (1) flow prediction parameters, (2) erosion prediction parameters, and (3) soil parameters. Parameter definitions are found in Appendix I, Table 6.

The Morris sensitivity analysis generates a scatter plot of the absolute mean and variance of the elementary effect of model output for each input parameter examined. The absolute mean gauges the relative sensitivity of a given input parameter on model output. For example, Figure 25 demonstrates that streamflow is most sensitive to the GQMN parameter (See Appendix I, Table 6). The variance illuminates parameter-parameter interactions or parameters that have non-linear effects on output. Figure 25, for instance, indicates that the REVAPMN and GWDELAY parameters are interacting parameters and are closely associated with the ALPHABF, ESCO, and K_{sat} parameters, all of which are involved in groundwater modeling (Appendix I, Table 6).

Flow Parameters

The importance of the CN parameter in model processes cannot be over-emphasized; it is used for surface runoff modeling in SWAT which is also employed in sediment generation calculations (R factor). It is, thus, unsurprising that streamflow and sediment yield predictions are very sensitive to the CN parameter, yet baseflow is much less so (Figure 25, Figure 26, Figure 27 and Appendix III, Figure 32). While SWAT can adapt CN values to different land-covers and soils, the model does not account for the effects of seasonal conditions on CN values. The extreme seasonality exhibited in the PCW and consequential changes in antecedent soil moisture conditions compromise the accuracy of the CN approach (Calvo et al., 2005). Calvo et al. (2005) theorize that this is attributed to soil hydrophobicity exhibited during heavy rain events in the early wet season in the PCW (Jaramillo et al., 2000). Although SWAT does account for antecedent moisture conditions thereby making it better equipped to predict runoff (Mishra et al., 2004), soil characteristics that change with seasonality cannot be modeled in SWAT[9]. Moreover, the sensitivity and uncertainty associated with the soil hydraulic properties (discussed below) such as AWC (Figure 25), factors into CN uncertainty under various soil moisture conditions. Although CN values are one of the most sensitive parameters in this analysis,

[9] The user can define different soil hydrologic groups (See Appendix I) according to seasons. However, the model only permits this action with hydrologic group A. Soils in the CQ area are primarily group C.

there is similarly has a large amount of uncertainty associated with their values (Appendix III, Figure 32).

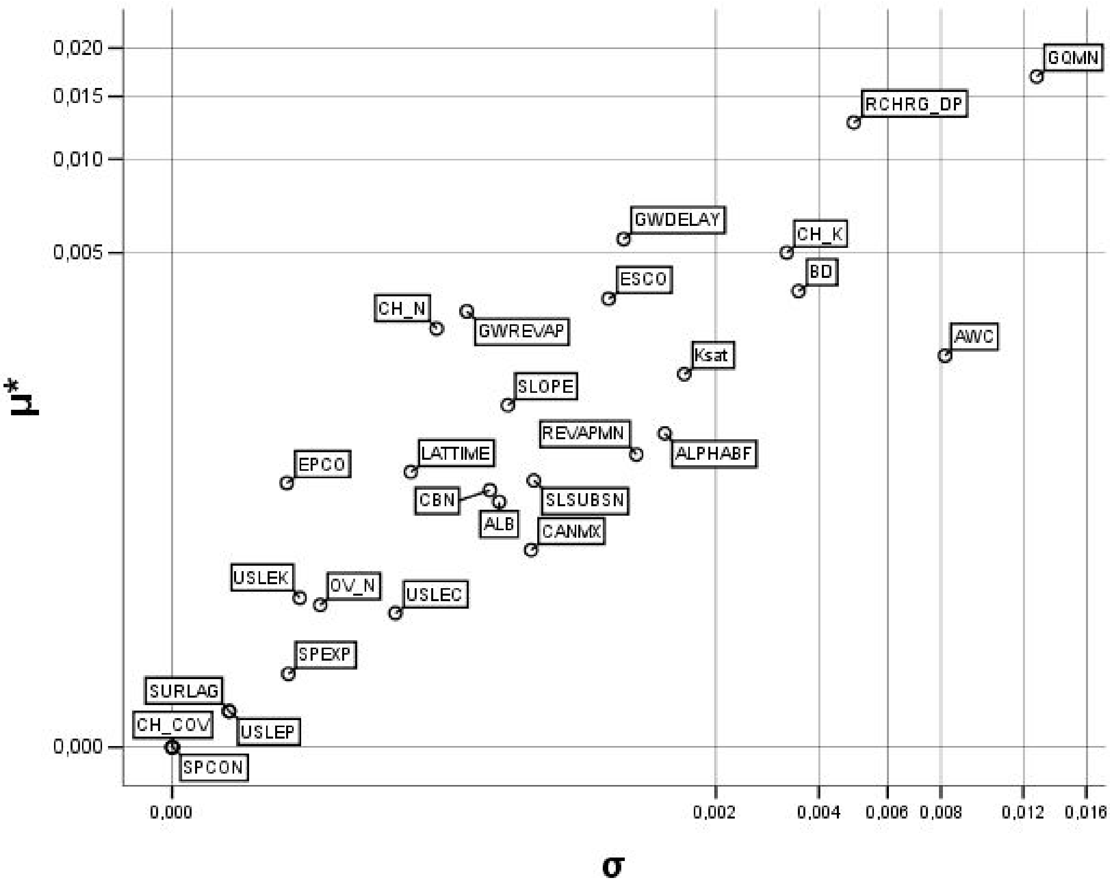

Figure 25: Morris plot for variable impact on streamflow out the watershed outlet. Parameter definitions are found in Appendix I, Table 6.

The sensitivity of model output, with the exception of sediment yield, to groundwater parameters (important for partitioning of baseflow and surface runoff components of streamflow) is exhibited by the Morris sensitivity analysis. Among the sensitive parameters, GWDELAY and RCHRGDP highlight the large uncertainty associated with groundwater predictions (Appendix III, Figure 33 and Figure 34), more so than most other parameters. This large uncertainty is likely due to two factors. Firstly, as previously discussed, the groundwater portion of the SWAT model has been identified as a weakness (Chu and Shirmohammadi, 2004), As such, it may come down to modifying the model framework as a whole as apposed to the individual parameters *per se*, to reduce some of this uncertainty. On the other hand, as with the CN values, these parameters are also contingent on soil characteristics such as K_{sat} parameters, affecting infiltration and ultimately groundwater flow. These parameters have a large amount of uncertainty associated with them, as expounded upon below.

Erosion Parameters

The value of precise estimates for MUSLE factors is illustrated by the sensitivity analysis (Figure 25, Figure 26 and Figure 27). The management factor (C factor) and, to a much larger extent, the support practice factor (P factor) assume a lot of the uncertainty associated with sediment predictions (Appendix III, Figure 33 and Figure 34), and consequently are likely to contribute substantially to the error associated with sediment simulations.

According to the SWAT model, pineapple cover is the primary contributor to basin-wide sediment yield; thus the uncertainties of the MUSLE parameters for this plant are discussed. Due to limited data availability, estimates for the C factor for pineapple were taken from a review of the literature and, as with the CN parameter, default values provided by SWAT were used for the P factor. Although best estimates were taken, it cannot be assumed that these proxy values are adequate for the CQ basins. Indeed, determination of these factors will vary as a function of soil and climatic characteristics and according to the version of USLE (RULSE, MUSLE, or USLE-M) employed in calculations (Kinnell, 2007, Kinnell and Risse, 1998, Kinnell, 2003). Given that the C value was adapted from a RULSE study in Hawaii and Australia and that the P factors are SWAT default values (generated with USLE), some uncertainty is surely associated with these parameters. This points to yet another probable cause of the poor model performance for sediment yield.

Although model calibration always entails parameters adjustments, for distributed models where parameters are numerous and data input demands are extensive, selecting the appropriate parameters and their values can sometimes be subjective and depends on the modeler's skill level and knowledge. Without sufficient amounts of precise data, this will incorporate uncertainty into the model. With no estimates of the MUSLE factors, refinement of other soil erosion parameters remains uncertain. For example, it was necessary to modify both the C and P factors for pineapple, however, minor adjustments in these parameter values engendered considerable changes in model output (Figures 25-27 and Appendix III). Obtaining local estimates for these parameters would eliminate some of the uncertainty associated with calibration and would allow the user to pinpoint other parameters to fine-tune the model.

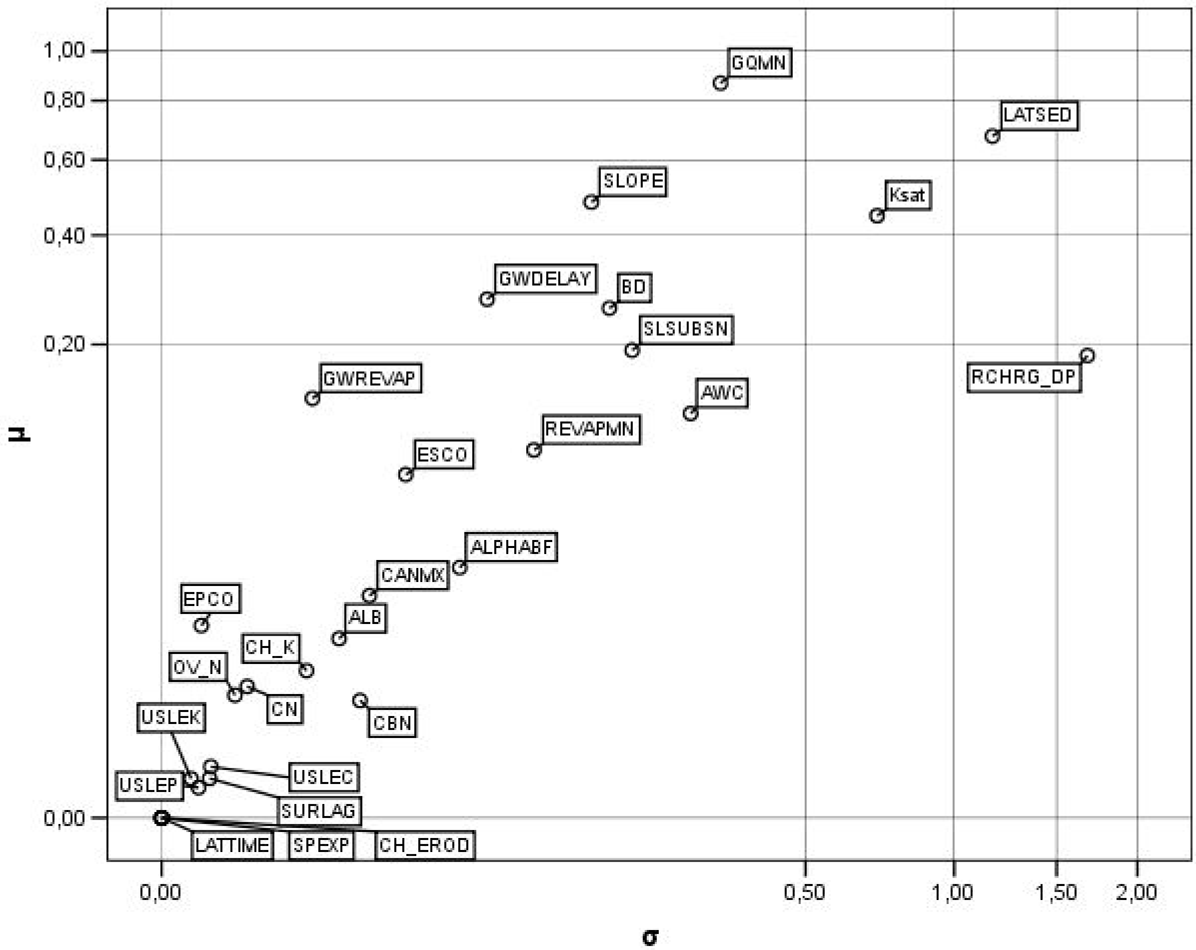

Figure 26: Morris plot for variables affecting groundwater flow. Parameter definitions are found in Appendix I, Table 6.

Soil Parameters

Some amount of model error in this study is associated with the soil parameter values, the extent of which cannot be assessed without additional data but can be discussed theoretically. While the sensitivity of the calibrated model to these factors is important (Figure 25, Figure 26 and Figure 27), in a comparison of the uncertainty of soil parameters it becomes evident that there is much more uncertainty associated with the BD parameter (Appendix III, Figure 37), particularly for sediment yield predictions, when compared to the K_{sat} and AWC parameters (Appendix III, Figure 38 and Figure 39). This may ultimately be justified by the associated effects of cattle ranching and pineapple management activities in the CQ basin, which may disturb and compact the soils, but cannot be simulated. Given the unreliability of the soil data in the region, this could not be incorporated into the model.

The soil data for the region is limited in spatial detail, both in terms of the area covered and the depth of the soil profile examined. IDIAP (1996) tested only the first few centimeters of the soil profile and determined texture and organic matter content, but no hydrologic properties were considered. Because soil characteristics can vary greatly through horizontal and vertical space, such a detail deficient dataset could have a substantial effect on model precision. More importantly, achieving accurate spatial estimates of a heterogeneous soilscape is a function of both the chosen interpolation method and the number of sample points. Kravchenko and Bullock (1999), found that interpolation using the inverse distance weighting method, as used by IDIAP (1996), to determine soil properties was not as accurate as other available methods. They also found that the distance between sample points is a significant factor for accurate predictions while the distribution of data points (i.e. at regular or irregular intervals) has a nominal effect on accuracy (Kravchenko and Bullock, 1999). Given that IDIAP (1996) estimated texture (used to estimate all other soil parameters) with an interpolation of only eight soil samples, soils of the region may not be adequately represented by the IDIAP soil data.

The PTFs used to estimate soil parameters were derived from USGS soil data which, according to some studies, makes them unsuitable to estimate characteristics of tropical soils (Tomasella and Hodnett, 1998, Tomasella et al., 2003, Hodnett and Tomasella, 2002). Kaolinitic clays are highly permeable due to their microaggregated structure, tend to drain more readily from saturation, and have lower BD and AWC when compared to clayey soils from temperate zones with similar or equivalent clay content (Hodnett and Tomasella, 2002). Consequently, the temporal zone PTFs are liable to over-estimate soil hydraulic properties (Tomasella and Hodnett, 1998). In accordance with these findings, substantial adjustments of these parameters (Appendix I, Table 5) yielded tremendous improvements to model performance. However, the model is very sensitive to changes in soil hydraulic parameters (Figure 25, Figure 26 and Figure 27); thus with out accurate estimates of AWC, BD, and K_{sat}, identification and refinement of other parameters affecting soil water movement remains uncertain.

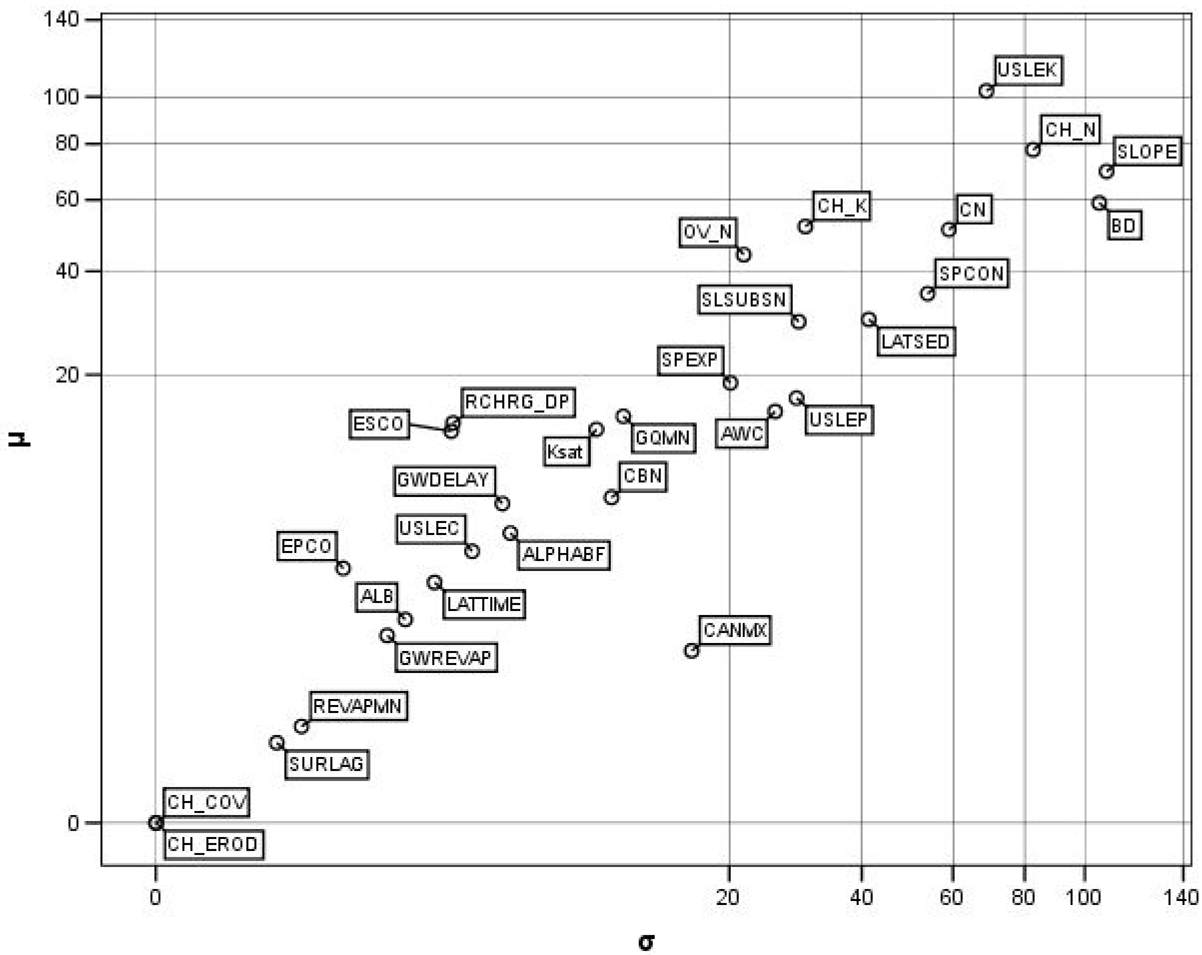

Figure 27: Morris plot for variable impact on sediment being transported out of the reach. Parameter definitions are found in Appendix I, Table 6.

6.0 Conclusions and Recommendations

The SWAT model was calibrated for the CQ river basin in the context of the PES and watershed management planning pilot projects in the TCH subbasins of the PCW. The calibrated model demonstrated acceptable performance for mean weekly streamflow and baseflow simulations. On the contrary, monthly sediment yield was poorly simulated. In the context of the PCW, however, where long-term cumulative sediment yield is important, the results demonstrate that SWAT could be a tool for use in the CQ basin and, probably, the greater PCW.

Although, SWAT could complement watershed management planning and conservation activity decision making, there are several improvements to the model that will need to be addressed before its application can be reliably used in the TCH and PCW context. Applying the model to predict more detailed processes, such as the effects of tillage or cropping patters on sediment yield (as required for PES program planning) or land-use change scenarios (required for best management practice recommendations) would necessitate: a) thorough estimates of current erosion in the TCH basins for pineapple crops and under different land management scenarios; b) consideration of the effects direct (grazing) and secondary (trampling) effects of cattle on sediment generation; and c) improved parameter estimates to reduce model uncertainty. This latter point includes MUSLE factors specified for the pineapple crop under local conditions and more spatially explicit detail of soil characteristics.

Building an accurate model involves not only calibration of sediment yield data measured at the basin outlet (as used in this study), but also of sediment yield for discrete land-covers across the basin. Given that no estimates are currently available for sediment yield from different land-uses in the area, a large amount of model uncertainty lays in the fact that SWAT cannot directly simulate the effects of cattle grazing. In the PCW, where pasture is one of the principal land covers, this represents a noteworthy impediment. Notwithstanding this obstacle, however, dividing pasture into cover classes (e.g. good, medium or poor vegetative cover) identified using remote sensing technology, or dividing pasture according to cattle density could allow modellers to account for some of the erosive effects of trampling or overgrazing. This would need to be coupled with data on the actual loadings from different classes of pasture cover. Currently, research is being undertaken by IDIAP to estimate annual sediment and water yield from pineapple, pasture, and forest cover and to assess the extent of soil compaction in the region, the results of which will be imperative for further model development.

In applying this model to planning in the greater PWC, where cumulative sediment yield would be most important, fine resolution sediment yield data may not be so crucial. Conversely, estimates of actual erosion on pineapple farms and lands used for grazing, while not currently available, would be particularly central to using SWAT for the development of a PES project in the TCH basins. Under the context of PES, farmers will potentially be earning money for implementing soil conservation techniques and their payments will likely be contingent on successful sediment yield reductions (e.g. the expected reduction within a given range would be determined by the model). Yet, if the model provides only ball-park estimates of the expected sediment yield reductions for a given conservation technique, monitoring mechanisms implemented by the PES program could find that specified reductions are not being met. This would be especially true in the (likely) case of limited financial resources which would rely on coarse monitoring techniques. It may be assumed, then, that farmers are not adhering to their side of the bargain (soil-conservation) even if they indeed were. Given that a PES program could directly alter peoples' livelihoods in the basin, it seems particularly pertinent to understand the true nature of different erosion-prevention mechanisms *in situ* and calibrate the model accordingly.

The analysis undertaken here has demonstrated the extreme sensitivity the model holds to certain factors – above all, erosion parameters and, to a lesser extent, groundwater and soil properties parameters. Model consistency and reliability for use in the PCW will bank on easing these uncertainties. The imprecision of MUSLE factor parameter estimates is most likely a considerable source of error for sediment yield predictions. This will likely be rectified with the results of the already commenced IDIAP-led study to determine some of the MUSLE factors for pineapple, forest, and pasture cover in the TCH region. Another important issue compounding model inaccuracy and uncertainty is associated with the pineapple plant growth model component, as discussed in Appendix II. The quantitative analysis undertaken in Appendix II reveals that improving sediment yield simulations for the TCH may go beyond simply the precision of input parameters (such as MUSLE factors) and question the applicability of the SWAT model framework, which appears to be restricted in it's ability to sufficiently simulate the pineapple plant.

Obtaining accurate estimates for soil property parameters remains difficult given that requisite data gathering is generally financially and logistically unfeasible in Panama, as in many other tropical developing nations. This evidence points to a need to develop superior PTFs for tropical regions, as stated by Tomasella and colleagues (1998, 2003), to better estimate these essential soil properties at minimal costs.

This study, as others have also mentioned, has identified the groundwater component of SWAT to be an underlying flaw of the model. Programmers and future researcher should dedicate efforts to improving these simulations by allowing modelers to incorporate explicit detail on aquifer systems and groundwater flow when available. Such modifications will be of utmost value for improving the SWAT model for use in the PCW and elsewhere.

In addition to the abovementioned applications, SWAT could also be applied for risk analysis, a valuable application given that Canal operations rely on flow timings, seasonal water yield, and ground water recharge for dry season baseflow, making the area vulnerable to recurring extreme events[10]. A comparison of the cumulative probability distributions of simulated and estimated weekly water yield illustrates that SWAT is a suitable tool for such analyses because it is able to predict events and amounts with a probability analogous to the observed distribution.

[10] what constitutes an extreme event in this case would be cumulative water yield above or below a certain threshold relevant only for water storage purposes

Climate models or land-use scenarios could be used as adjuncts to SWAT to forecast reservoir spilling requirements during the wet season or the longevity of Canal operations during the dry season under alternative land-use/management scenarios or in years of predicted climatic extremes. The model would therefore be an appropriate tool to assist in the planning of water supply allocation so as to avoid the unfavorable outcomes of climatic events (i.e. El Niño), such as those experienced in 1982 and 1997. Despite these assertions, the tendency to over-predict flow for extreme precipitation events could, over long periods of time, prove to be problematic. As such, SWAT would require further calibration with a more temporally and spatially detailed dataset so as to observe model behavior and predictions for other extreme events and to confirming its long-term reliability as a predictor.

In assessing the feasibility of all of these options, it is important to mention that the greater PCW also has large forested zones which provide much of the annual water yield (via cloud forests) and protect the steep mountainous regions of the PCW. Employing SWAT in this context would be a challenge, given that the default land-cover choices in the model program are currently limited to species of the occident (trees, crops, plants, etc.). This could integrate another level of uncertainty into the model for use in the tropics, where vegetation may significantly differ – in terms of their role in hydrological and erosion processes – from that of temperate zones. Attempts could be made to modify the model to simulate tropical forests, although this would require working within the SWAT model framework. Extrapolating from the lessons learned in pineapple simulations (Appendix II), the model is limited. Instead of taking these routes, other models could alternatively be combined as a complement to the SWAT model. For example, TOPMODEL has been successfully adapted to model water yields in the forested regions of Panama (Kinner and Stallard, 2004) and could serve such a purpose. This study recommends a similar solution for pineapple plant simulations (See Appendix II, Section iv). Given that SWAT is a comprehensive model that is better tailored to meet most of the needs of watershed management planning in the greater PCW (see Section 3.3, Model Selection), combining various other models and building on the SWAT model as a backbone to meet the diverse modeling needs of the greater Panama Canal region would be practical. This however, would demand substantial financial and human resources, which may not necessarily be forthcoming in Panama.

Above and beyond what has already been mentioned, successfully applying this model, in tandem with others or alone, to develop and implement conservation plans, such as PES, risk analysis, or best management practice recommendations for the area presents two additional hindrances. As already highlighted throughout this study and in this conclusion, issues of data scarcity present an important barrier for effective and efficient use of GIS and spatial tools in TCH and the PCW. Although process-based models such as WEPP have been heralded as superior predictors of physical processes such as erosion, in scenarios such as that of Panama their application is often unfeasible because their input and data demands are more extensive than for distributed models (such as SWAT). Information shortages in Panama pertain not only to the GIS data and sediment yield and streamflow data necessary to calibrate a distributed model such as SWAT, but also complementary datasets, socio-economic information for example. This knowledge has been characterized as important for sustainable planning of any watershed or conservation activities, especially PES (Wunder, 2005).

While collecting data in Panama for this study, another impediment to project implementation and planning became salient which pertains to cooperation between public and private institutions within the PCW. Currently, IDIAP has procured the funding necessary to plan and implement a PES pilot project in the TCH basins. However, owing to a lack of collaboration between participating entities, the ACP with support from CICH has embarked on a similar endeavor, in the same subbasins, with equivalent objectives, and engaging similar actors. Although the formation of CICH was an attempt to create a 'holistic' team of integrated watershed managers, this group instead has elitist and exclusive tendencies (GreenCOM, 2002) and precludes some other relevant institutions or stakeholders from decision-making. IDIAP is a perfect example of a public institution which has been pushed to the sidelines and is struggling to manage and maintain their projects afloat in the face of more powerful entities such as the ACP. This is well illustrated in the PES pilot project. Amalgamating forces and combining resources could be a means to effectively implementing projects such as PES, but this has yet to become a reality in Panama. This is, in effect, a significant pitfall for successful program implementation in the country as a whole, as others have already asserted (GreenCOM, 2002). This leads to inefficiencies and tensions between institutions. Thus, there exists a serious need to foster camaraderie between participating organizations if future projects are to make the best use available human and financial resources.

Appendix I: Supplementary Tables

Table 3: Definitions used for the conversion of soil drainage class to a corresponding soil hydrologic group. Descriptions are from the CATAPAN handbook (CATAPAN, 1970) and the SWAT user manual (Neitsch et al., 2002).

CATAPAN Soil drainage class	USDA and NRCS Soil hydrologic groups
E (Excessively Drained), water is removed from the soil rapidly enough to be a limiting factor in plant growth. Excessively drained soils are commonly very steep, very porous, very shallow, or a combination of these.	**A,** soils having high infiltration rates even when thoroughly wetted, consisting chiefly of sands or gravel that are deep and well to excessively drained. These soils have a high rate of water transmission (low runoff potential).
W (Well Drained), water is removed from the soil readily, but not rapidly. Well drained soils are commonly intermediate in texture. Exceptions are the functionally well drained, fine clay Oxisols found on the Panamanian "Red Plains". Well drained soils commonly retain optimum amounts of moisture for plant growth	**B,** soils having moderate infiltration rates when thoroughly wetted, chiefly moderately deep to deep, moderately well to well drained, with moderately fine to moderately course textures. These soils have a moderate rate of water transmission.
M (Moderately Drained), water is removed from the soil somewhat slowly so that the profile is wet for a small but significant part of the time. Moderately well drained soils commonly have a slowly permeably layer within the solum which restricts water movement and retards percolation of water is overlying layers, and may cause them to show the effects of poor drainage, that is, grey colored mottling indicating reduction.	
N (Imperfectly Drained), Somewhat poorly drained. Water is removed from the soil slowly enough to keep it wet for significant periods but not all of the time. Imperfectly drained soils commonly have a slowly permeable layer within the profile, a seasonal high water table, addition of water through seepage, or a combination of these conditions. Unless artificially drained, crop production is limited to those crops which have a tolerance for periodic excess by water.	**C,** soils having slow infiltration rates when thoroughly wetted, chiefly with a layer that impedes the downward movement of water or of moderately fine to fine texture and a slow infiltration rate. These soils have a slow rate of water transmission (high runoff potential).
G (Poorly Drained), water is removed slowly so that the soil remains wet for a large part of the time. The water table is commonly at or near the soil surface for extended periods during the year. Poorly drained conditions are most often due to high water table; to a	**D,** soils having very slow infiltration rates when thoroughly wetted, chiefly clay soils with a high swelling potential; soils with a high permanent water

slowly permeable layer within the soil profile; to seepage; or to some combination of these conditions. Soils which are poorly drained commonly occupy level or slightly depressed relief, and may have darker colored surface horizons than their better drained neighbors. The excess water prohibits the growing of all but the most water-tolerant field crops.	
V (Very Poorly Drained), Water is removed from the soil so slowly that the water table is at or near the soil surface the greater part of the time. Subsoil colors are usually gray and the surface distinctly grey or darker than surrounding soils.	table; soils with a clay pan or clay layer at or near the surface; and shallow soils over nearly impervious materials. These soils have a very slow rate of water transmission.

Table 4: Values used in the construction of the pineapple crop database for use in the SWAT model.

Name	Variable definition	Value	Reference
BIO_E	Radiation-use efficiency or biomass-energy ratio (kg/ha)/(MJ/m^2)	56	Modified during evaluation procedures from 18 (Yu et al., 2000)
HVSTI†	Harvest index for optimal growth conditions	0.45	(Py et al., 1987) Page 57 and (Yu et al., 2000)
BLAI‡	Maximum potential leaf area index	8	(Yu et al., 2000)
FRGRW1*	Fraction of plant growing season corresponding to LAIMX1 value	0.23	(Zhang and Bartholomew, 1997)
LAIMX1*	Leaf area index upon emergence (refer to pg. 183 of SWAT input manual for description)	0.32	
FRGRW2*	Fraction of plant growing season corresponding to LAIMX1 value	0.68	
LAIMX2*	Leaf area index before harvest see pg. 183 of SWAT input manual)	0.63	
DLAI	Fraction of growing season when leaf are begins to decline	1	
CHTMX	Maximum canopy height (m)	0.10	(Yu et al., 2000)
RDMX	Maximum root depth (m)	0.085	(Yu et al., 2000)
T_OPT≠	Optimal temperature for plant growth (ºC)	30	(Sanford, 1962) and (Yu et al., 2000)
T_BASE≠	Minimum (base) temperature for optimal plant growth (ºC)	7	(Sanford, 1962) and (Yu et al., 2000)
CNYLD	Normal fraction of nitrogen in yield (kg N/kg biomass)	0.0015	Adapted from (Py et al., 1987) Page 157
CPYLD	Normal fraction of phosphorus in yield (kg N/kg biomass)	0.0002	
PLTNFR (1)	Normal fraction of nitrogen in plant biomass at emergence (kg N/kg biomass)	0.0170	
PLTNFR (2)	Normal fraction of nitrogen in plant biomass at 50% maturity (kg N/kg biomass)	0.0150	
PLTNFR (3)	Normal fraction of nitrogen in plant biomass at maturity (kg N/kg biomass)	0.0071	

LTPFR (1)	Normal fraction of phosphorus in plant biomass at emergence (kg N/kg biomass)	0.0007[11]	
PLTPFR (2)	Normal fraction of phosphorus in plant biomass at 50% maturity (kg N/kg biomass)	0.0006[11]	
PLTPFR (3)	Normal fraction of phosphorus in plant biomass at maturity (kg N/kg biomass)	0.0005[11]	
WSYF	Lower limit of harvest index	0.265	(Malezieux et al., 2003) Page 93
USLE_C	Minimum value of USLE C factor for water erosion	0.100	(Rattan, 1990) Pages 259 and 264
GSI	Maximum stomatal conductance at high solar radiation and low vapor pressure deficit (m/s^{-1}) (refer to pg. 191 of SWAT input manual)	0.16	Adapted from (Malezieux et al., 2003) Page 83
VPDFR	Vapor pressure deficit (KPa) corresponding to second point on the curve (refer to pg. 192 of SWAT input manual)	4	SWAT user manual
FRGMAX	Fraction of maximum stomatal conductance at VPDRF (refer to pg. 193 of SWAT input manual for description)	0.75	SWAT user manual
WAVP	Rate of decline in radiation-use efficiency per unit increase in vapor pressure deficit (refer to pg. 194 of SWAT input manual)	6	SWAT user manual
CO2H1	Elevated CO_2 atmospheric concentration corresponding to second point on the radiation-use efficiency curve (refer to pg. 194 of SWAT input manual). Used only for climate change studies.	660	SWAT user manual
BIOEH1	Biomass-energy ration corresponding to the second point on the radiation-use efficiency curve (refer to pg. 195 of SWAT input manual). Used only for climate change studies.	10.5	SWAT user manual
CN (A)	SCS curve number at moisture condition II for soil hydrologic group A	25	(Giambelluca et al., 1886)
CN (B)	SCS curve number at moisture condition II for soil hydrologic group B	59	

[11] The fraction of phosphorus in plant biomass is minimal and the amount fluctuates during plant growth; however restrictions in the SWAT model require that this variable decreases over time. Actual derived values are PLTPFR(1): 0.00022, PLTPFR(2): 0.00093, and PLTPFR(3): 0.0065 (adapted from PY (1987) Page 157). The values in the table above were thus chosen according to the lower limit for this parameter in SWAT, 0.005.

CN (C)	SCS curve number at moisture condition II for soil hydrologic group C	72	
CN (D)	SCS curve number at moisture condition II for soil hydrologic group D	79	
Manning's "n"	Roughness coefficient for overland flow from Manning's equation	0.15	SWAT user manual

† Harvest indices vary between 0.4 and 1 (Hepton, 2003) according principally to diurnal temperature fluctuations and planting density. Yu et al,. (2000) employed 0.45 for erosion simulation using the WEPP model.

‡ LAI values may be as high as 12 at floral induction, but values of 6-8 are more common (Malezieux et al., 2003). For example, in Mexico mulching the soil during the crop growing season was found to raise the LAI from 8.5 to 9.5 (Rebolledo-Martinez et al., 2005). Yu et al., (2000) used 8.0 as a maximum leaf-area index.

* These factors were derived from a graphic published by (Zhang and Bartholomew, 1997).

≠ These values were used by Yu et al., (2000), and are concurrent with the literature. However, in the ALOHA model, which was successfully used to simulate pineapple crop growth in Hawaii, Africa and Australia, 16ºC was used as the base temperature and 35ºC as the optimum temperature (Zhang et al., 1997).

CNYLD/CPYLD and PLTNFR/PLTPFR: These factors were derived from a graphic from Py (1987), page 157. Please see the footnote 1 for further explanation.

WSYF: The lower limit of the harvest index, expected due to water stress, was derived from Kadzmin (1975), adapted from Malézieux et al., (2003); where total dry matter was reduced by 46.9% in the unirrigated treatment.

GSI: This factor was derived using the inverse of the stomatal resistance as described by Malézieux et al., (2003).

Table 5: Parameters modified during calibration procedure. The basin-wide average value is given for the SLSUBBSN, SLOPE, SOL_K, SOL_AWC, and SOL_BD default values. In cases where the final value is presented as a percentage, this is percent of the default value. Parameter definitions are found in Appendix I, Table 6.

Parameter	Default	Final Value
SOL_K	250	-70%
SOL_AWC	0.10	+250%
SOL_BD	1.48	-20%
ALPHA_BF	0.048	0.044
SLSUBBSN	30	-10%
SLOPE	0.082	-10%
CN	90 - 48	-2%
GW_DELAY	31.0	40.0
RCHRG_DP	0.05	0.25
GWQMN	0.0	20.0
GW_REVAP (Forest)	0.02	0.1
SURLAG	4	10
LATTIME	0	12
EPCO	1.5	+50%
ESCO (Pasture)	0.95	0.5
USLE_C (Pineapple)	0.3	0.35
USLE_P (Pineapple)	1.0	0.93

Table 6: SWAT model parameters employed in the exploratory Morris sensitivity analysis.

Parameter	Definition	Range
SOL_K	Soil saturated hydraulic conductivity (mm/hr)	0.00 – 2000.00
SOL_AWC	Available water capacity of the soil layer (mm H_20/mm soil)	0.00 – 1.00
SOL_CBN	Organic carbon content of soil (% soil weight)	0.05 – 10.00
SOL_ALB	Moist soil albedo	0.00 – 0.25
SOL_BD	Soil moist bulk density (Mg/m^3)	1.10 – 2.5
ESCO	Soil evaporation compensation coefficient, which allows variation for the soil evaporative demand to account for capillary action, crusting, and cracks. Lower coefficient allows the model to extract more of the evaporative demand from lower soil levels.	0.00 – 1.00
ALPHA_BF	Baseflow alpha factor. The baseflow recession constant (α_{gw}), is a direct index of groundwater flow response to changes in recharge. Values vary from 0.1-0.3 for land with slow response to recharge to 0.9-1.0 for land with a rapid response.	0.00 – 1.00
GW_REVAP	Ground water "revap" coefficient. Allows water to move from shallow aquifers into the overlying unsaturated zone. Lower coefficient restricts the movement of water, while higher coefficient allows the rate of water transfer to approach potential evapotranspiration.	0.02 – 0.20
REVAPMN	Threshold water depth of the shallow aquifer for "revap" or percolation to the deep aquifer to occur (mm H_20).	0.00 – 500.00
GWQMN	The threshold water depth in the shallow aquifer required for flow to occur (mm H_20). Groundwater flow is allowed only if the water depth in the shallow aquifer is equal to or greater than this threshold.	0.00 – 5000.00
GW_DELAY	Groundwater delay time (days). Water that moves past the lowest depth of the soil profile by percolation or bypass flow enters and flows through the vadose zone before becoming shallow aquifer recharge. The lag between the time that water exits the soil profile and enters the shallow aquifer will depend on the depth to the water table and the hydraulic properties of the geologic formations in the vadose and groundwater zones.	0.00 – 500.00
LAT_TIME	Lateral flow travel time (days). Setting LAT_TIME = 0.0 will allow the model to calculate the travel time based on soil hydraulic properties.	0.00 – 180.00
RCHR G_DP	Deep aquifer percolation fraction. The fraction of percolation from the root zone which recharges the deep aquifer.	0.00 – 1.00
CN	Initial SCS runoff curve number for moisture condition II.	0 – 100

CANMX	Maximum canopy storage of a given land-cover (mm H_20).	0.00 – 100.00
CH_K	Effective hydraulic conductivity of the tributary alluvium	0.00 – 500.00
SURLAG	Surface runoff lag time (days)	1.00 – 24.00
EPCO	Plant uptake compensation factor.	0.00 – 1.00
USLE_P	USLE equation support practice (P) factor.	0.10 – 1.00
USLE_K	USLE equation soil erodibility (K) factor.	0.00 – 0.65
USLE_C	USLE equation cropping practices (C) factor.	0.001 – 0.500
CH_COV	Channel cover coefficient. This factor is defined as the ratio of degradation from a channel with a given vegetative cover to the corresponding degradation from a channel with no vegetative cover. Lower values indicate that the channel is more protected from degradation through vegetative cover, while higher values indicate more channel protection.	-0.001 – 1.000
CH_EROD	Channel erodibility coefficient. This factor is conceptually similar to the USLE equation soil erodibility factor (K). Lower values indicate a less-erosive channel, while higher values indicate less resistance to erosion.	-0.05 – 0.60
SPCON	A linear parameter used in calculating the maximum amount of sediment that can be reentrained during sediment routing[12].	0.001 – 0.010
SPEXP	Exponent parameter for calculating sediment reentrained in channel sediment routing[1].	1.0 – 1.5
SLSUBBSN	Average slope length (m). With terracing slope length is equal to the terrace interval.	10.00 – 150.00
SLOPE	Average slope steepness (m/m). May be varied by land-cover.	0.00 – 0.60
CH_N	Manning's "n" value for the main channel.	0.01 – 0.30
OV_N	Manning's "n" value for overland flow.	0.01 – 30.00
APM	Peak rate adjustment factor for sediment routing in the subbasin.	0.50 – 2.00
PRF	Peak rate adjustment factor for sediment routing in the main channel.	0.00 – 2.00

[12] Maximum sediment equation: $conc_{sed,ch,mx} = c_{sp} \, v_{ch,pk}^{spexp}$, where $conc_{sed,ch,mx}$ is the maximum concentration of sediment that can be transported by water (tons/m^3 or kg/L), c_{sp} is the SPCON factor, $v_{ch,pk}$ is the peak channel velocity (m/s), and *spexp* is the SPEXP factor.

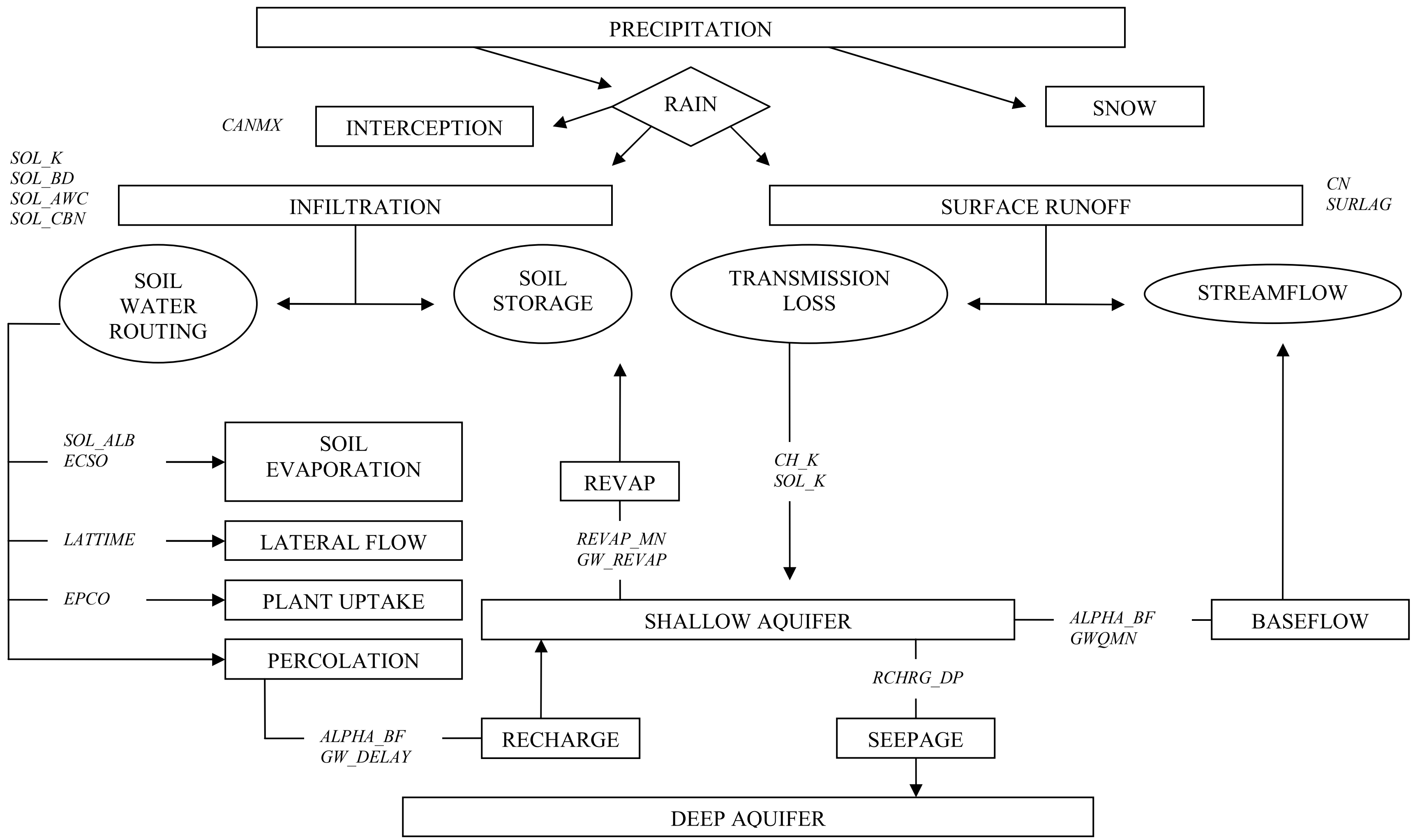

Figure 28: Schematic of major water movement pathways used in SWAT. Each box represents a major model component; parameters employed in calibration procedures and sensitivity analysis corresponding to each component are identified in italics. A description of each parameter may be found in Table 5. Adapted from Neitsch et al. (2000).

Appendix II: Pineapple Simulations

This appendix is devoted to information and procedures related to the simulation of pineapple growth and land management practices. Four components are addressed: (i) the actual land management practices employed in TCH, (ii) the creation of SWAT land management scenarios to simulate actual land management practices, (iii) evaluation of the SWAT pineapple growth model, and (iv) challenges and prospects for simulating pineapple growth and land management practices using SWAT. Because available data was collected at the tri-basin (TCH) level, the following discussion focuses on all three basins rather that solely CQ.

i. Land Management Practices in the TCH Basins.

An accurate representation of the practices farmers employ on their land is a central component of modeling the effects of land management on watershed hydrology and sediment movement. The management practices used in TCH as described below.

Land Preparation

Fields in TCH are prepared prior to planting, beginning with manual clearing of weeds and brush, followed by residue burning and tillage. About half of the pineapple producers in TCH plough fields one to three times at a depth of 6 to 8 inches using a disc plough (Martez and Vergara, 2004) while others use non-mechanized methods. About 38% of producers, all large-scale, also practice subsoiling at unsustainable rates, up to three times before planting at a depth of 8 to 12 inches (Martez and Vergara, 2004). Prior to planting, approximately 36% of producers prepare planting beds and, if not already in place, ditches are dug (Martez and Vergara, 2004). Preparing the terrain in this manner can help maintain well-drained soils and foster healthy growth of the pineapple plant, which is sensitive to waterlogged soils (Bartholomew et al., 2003). Only 2% of producers prepare their land for contour cropping (IDIAP, 2007).

Planting

Once the land has been prepared, planting is done by hand at a median density of 60,000 plants/ha (IDIAP, 2007). Because the pineapple is a self-propagating plant, a cutting is taken from a mature plant and used as planting material for the subsequent crop cycle. Planting generally commences at the beginning of the wet season (April or May) but may start as late as September. Commercial growers who use irrigation technology, about half of all producers (Martez and Vergara, 2004), are able to prepare their land and plant crops at anytime of the year. In such cases, plots are often planted (and thus harvested) at intervals, allowing the producer to have a year-round harvest and a constant market-supply. Because the pineapple is a drought-resistant plant (Bartholomew et al., 2003), irrigation is used minimally and is not considered to significantly alter water flows in the area. Accordingly, irrigation practices are not included in the SWAT land management scenarios.

Soil Amendments and Agrochemicals

A detailed account of the types and concentrations of fertilizers and agrochemicals used and their application schedule for pineapple cultivation in TCH is available (IDIAP, 2007b). SWAT, however, is unable to model the effects of nutrient availability on plant growth[13] and only uses this information to simulate water quality. Because this does not comprise one of the current study objectives, these factors were not included in management scenarios.

Harvest

In the TCH basins, pineapple flowering is induced (used to shorten the natural pineapple life-cycle and synchronize the harvest) about 230 days after planting and within 4 to 5

[13] SWAT does not simulate the effects of nutrient availability on plant growth but does simulate plant nutrient uptake and reports nutrient concentrations in the crop yield. Similarly, SWAT is able to simulate water-uptake by plants, but cannot simulate the effects of drought stress or water excess on crop yields (Section iv)

months the fruit may be harvested. The terminal inflorescence of the pineapple allows for various production cycles, yielding multiple fruit harvests, or ratoon crops. In THC, ratoon cropping is not practiced because local geographical and climatic conditions favour a relatively rapid crop cycle – about 13 months compared a maximum of 17 months in other areas (Bartholomew et al., 2003). After the first harvest, planting material[14] is taken and within 6 days the crop residue is removed and usually incinerated. Preparation of the land and planting will commence shortly thereafter. It is important to note that fallow-cropping cycles are not generally practiced in TCH.

ii. SWAT Land Management Scenarios

SWAT is able to simulate actual or hypothetical land management practices in a watershed through land management scenarios. Scenarios detailing the terrain preparation, planting, and harvesting operations as described above were created. To account for the temporal variation of management schedules (exact start and end dates of each practice varies according to producer), a total of 30 individual scenarios were written, each following the same chronological order of activities but with distinct activity start and end dates (Table 7).

Table 7: A chronological outline of land management activities for pineapple fields in the TCH basins. The timing of each activity is indicated according to the number of days after planting (DAP), and the range of time periods which producers perform a given activity is shown as the minimum and maximum values. The count indicates the number of producers, out of the 50 interviewees, that participate in the given activity. Adapted from IDIAP (2007, unpublished).

Activity Description	Minimum/Maximum (DAP)		Mean/Median/Mode (DAP)			Count
Mechanized tillage (with disk plow and/or subsoiler)	- 30	-1	-4.8	-3	-2	41
Land preparation - planting beds, contours, and/or drainage ditches	- 30	-1	-3.4	-1	-1	38
Planting operation	0	0	0	0	0	50
Harvest and kill operations (residue removal)	327	424	369.5	372	372	50

[14] This is a cutting from the mature plant consisting of the crown, stem, or other organ used for propagation of the subsequent crop.

Other important information may also be incorporated into land management scenarios. According to Cooley and Lane (1982), CN values for the pineapple crop change considerably as the plant matures. For soil hydrologic groups C and D (See Appendix I, Table 3), the CN values were found to be as high as 90 at the commencement of the growing season and as low as 48 upon reaching canopy maturity. Since SWAT allows the user to specify different CN values over time, the CN values reported by Cooley and Lane (1982) were included in land management scenarios to reflect these significant changes. Additionally, the user is able to define the initial planting material dry biomass and leaf area index (LAI) when a planting operation is simulated. For the pineapple, initial planting material biomass was defined at 2.7 kg/ha and the initial leaf area index at 0.2 (adapted from Bartholomew et al., 2003 and Py, 1981)

iii. Evaluation of the SWAT Pineapple Growth Model

SWAT is able to simulate plant growth but requires detailed plant-specific data to do so. In order to model pineapple growth the required data was taken from the literature (Appendix I, Table 4) and incorporated into the SWAT growth database. This section briefly highlights some features of the SWAT plant growth model and explains the methodology used for model evaluation. The primary objective of this study is to simulate sediment production and streamflow and not to create and validate a pineapple growth model; therefore only a limited evaluation of the model is performed and discussed here and some possible amendments to the model are suggested for future research endeavours.

Introduction

SWAT simulates plant growth from the basic components leaf-area index (LAI) development, intercepted solar radiation, and accumulation of biomass. LAI is assumed to follow a sigmoidal development curve and is driven by the number of heat units accumulated in a given day. Heat units are accumulated following the standard convention of summing daily mean temperature-degrees above the plants base temperature and are calculated by the equation:

$$HU_i = \overline{T}_i - T_{base} \text{ when } \overline{T}_i \rangle T_{base} \qquad \text{Equation 1}$$

Where HU_i is the number of heat units accumulated on day *i* and $\overline{T}_i$ is the average temperature on day *i*. T_{base} is the plant base temperature, which is a user-specified variable. Thus, the rate of change of the LAI can be calculated if the total number of heat units needed to bring a plant maturity is known.

In SWAT, 50% of radiation is assumed to be photosynthetically active and light interception per unit land area is dependent on LAI. Absorption of intercepted radiation is modeled by a simple Beer's Law (Monsi and Saeki, 1953) (Equation 2) model that assumes equal horizontal and vertical leaf-distribution, resulting in a light extinction coefficient K of -0.65. In the equation:

$$H_{photo} = 0.5 \cdot H_{day} \cdot (1 - e^{K \cdot LAI}) \qquad \text{Equation 2}$$

H_{photo} is the amount of photsynthetically active radiation intercepted by the plant, H_{day} is the total daily solar radiation and K and LAI are as described above.

Biomass accumulation is then calculated as a function of LAI and the user-defined radiation-use efficiency parameter, a fixed ratio for the conversion of light to biomass by the equation:

$$\Delta BM = RUE \cdot H_{photo} \qquad \text{Equation 3}$$

where ΔBM is maximum potential increase in biomass for a given day and RUE is the radiation-use efficiency parameter. The biomass accumulated for any plant is the sum of all daily maximum potential increases of biomass over the simulated growth period. A description of all parameters used to model plant growth is provided in Appendix I, Table 4.

Accurate simulation of plant LAI over time is important for plant growth simulations due to its mathematical relationship to multiple other plant growth parameters. In addition to those mentioned above, root development and changes in canopy cover and height are dependent on (linearly related to) the LAI development. Although SWAT does not print out changes in root development or canopy cover, it does provide daily print-outs of simulated LAI values which may, therefore, be used as an indicator of root and canopy cover growth. In addition to the CN values and MUSLE factors, accurate simulation of root and canopy development (via LAI), should be sufficient to simulate the effects of pineapple growth on erosion (Kiniry, 2006).

In general, the accuracy of a crop growth model may be validated by statistically comparing empirical data to the simulated output; this can include observed crop yields or plant biomass accumulation sampled from the field. Simulations must replicate the conditions under which the observed yields were grown in order to maintain consistency of the physical factors that may affect plant growth, specifically environmental conditions (climate variations, soil etc.), land management practices (nutrient applications, irrigation, planting density, etc.) and crop cycle. Observed data should only be compared with data simulated in the same geographic area and simulated over the same time period as the observed data.

As further expounded upon in Section iv, SWAT is unable to simulate pineapple plant growth over a two calendar year period. In TCH, the pineapple crop takes about 372 days after planting to reach maturity and thus the crop cycle cannot be simulated within one calendar year. This implies that a validation of the crop growth model cannot be effectively performed since observed yields cannot be compared to yields which were simulated under similar growing conditions. Of principal importance is the re-creation of climatic conditions, given that SWAT simulated plant growth is principally based on solar radiation and temperature.

Methodology

The following procedure was used to provide a speculative validation of the SWAT pineapple growth model. While this study specifically models flow and sediment in the

CQ basin, the plant growth model component was evaluated over the entire TCH basins, to maximize use of available data.

To maximize the growing season, all simulated pineapple crops were planted on January 1 and harvested on December 31 of the year 2006, the same year in which the field samples were grown[15]. No data monitoring physical or chemical changes throughout the pineapple growth cycle is available for the TCH basins, so trends in daily biomass production and LAI changes could not be compared to observed data. Mature plant biomass, however, is available. IDIAP (2007a) collected 72 mature pineapple plant samples in 2006 from 5 different farms (about 14 samples per farm) and measured their dry weights. The mean observed dry biomass from each farm was compared with the mean simulated biomass using a simple correlation analysis to approximate the model's ability and potential to simulate pineapple growth. The mean simulated biomass was calculated from crops grown with in the subbasins corresponding to the same geographic area (the same farm) as the observed data. Some of the model parameters important for plant growth, specifically LAI, radiation-use efficiency, and base-temperature parameters, were adjusted that so that simulated values would conform to the mean total dry biomass yield as measured in TCH. Their values are found in Appendix I, Table 4. It should be noted, that due to data scarcity, this analysis does not attempt to constitute a rigorous model evaluation.

Results

Using data collected in the TCH basins, a field of 60,000 plants/ha would to produce a mean dry plant biomass (fruit and above and below ground) of 57 Mg/ha, comparable to the mean simulated biomass of 52 Mg/ha. Increasing the radiation-use efficiency or the base temperature would be a quick-fix to make simulated biomass conform to the mean observed value; yet, examining the distribution of simulated and observed biomass values shows that this may not be the best solution to improve simulation accuracy. While the

[15] This was a necessity because, as described in Section iv, SWAT is unable to simulate plant growth over a 2 year period.

simulated and observed mean biomasses are somewhat similar, the distribution of simulated biomass values is clearly more narrow (Figure 29). Excluding extreme outliers, a biomass range of 34 Mg/ha to 70 Mg/ha can be calculated for pineapple plants sampled in TCH whereas simulated biomass values range from 41 Mg/ha to 58 Mg/ha (Figure 29).

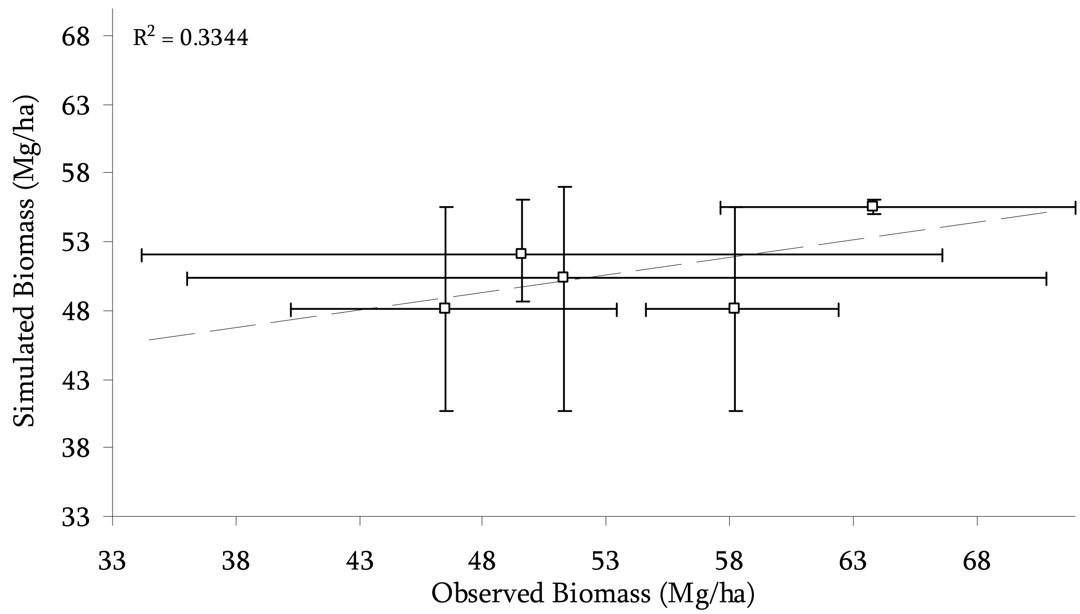

Figure 29: Scatter plot of mean observed and mean simulated dry biomass of the mature plant. Each point represents the group mean of total plant biomass sampled from a single farm (observed) or simulated within a single subbasin (simulated). X and Y bars show the range of observed and simulated biomass values above and below the mean of each group. The linear regression line and coefficient of determination are also shown.

An example of SWAT simulated daily biomass accumulation and LAI change for three pineapple crops grown in different HRUs is shown in Figure 30. In SWAT, a HRU represents a single spatial unit were all soils and crop characteristics are considered to be the same. These three examples were chosen to illustrate the range of SWAT simulated values. HRU 66 simulated biomass and LAI were the maximum of all simulated values while biomass and LAI simulated in HRU 211 were the minimum simulated values. HRU 10 is an example of a typical (average) pineapple growth simulation at the HRU level. Biomass accumulation in all three cases appears to follow a near-linear shape, but HRU 211 shows an inconsistent growth pattern between Julien day 25 and 85 (Figure 30). This pattern is also reflected in the corresponding LAI development curve which governs biomass accumulation (Figure 30). In all three examples, the LAI approaches a threshold by the end of the year as biomass accumulation peaks. The maximum LAI for a mature plant under optimal growing conditions is a user-defined variable which was set as 8 for the pineapple plant (Appendix I, Table 4).

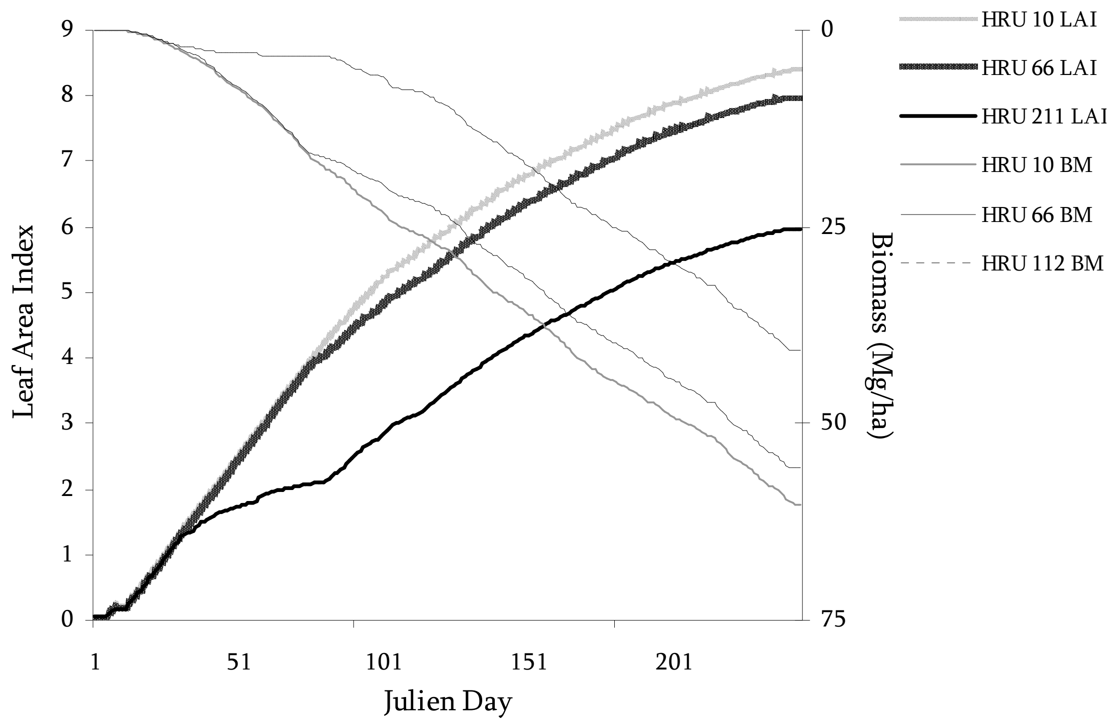

Figure 30: Three examples of daily leaf-area index (LAI) and biomass (BM) accumulation simulated by the SWAT pineapple growth model at the HRU level.

Figure 30 demonstrates that not all simulated crops reach the user-defined, maximum LAI – which directly affects total biomass accumulation. Most saliently, the biomass and LAI curves of HRU 211 are visibly distinct from the same curves of HRU 66 and HRU 10. An immediate supposition may be to attribute these differences to soil types, water stress, nutrient availability, or some other environmental or land management factor. However, SWAT does not model the impact of these factors on plant development. Instead, plant growth is dependent only on the amount of intercepted solar radiation, the rate at which the plant converts this energy into biomass (or the plant radiation-use efficiency) and the base temperature used to calculate heat units. The latter two factors are user-defined and set at the same value for all simulated pineapple crops (Appendix I,

Table 4). Solar radiation reaching the plant, however, is not a user-defined variable and is instead determined, principally, by cloud cover.

Although SWAT does not read out daily climatic information (precipitation is the exception), examining the behavior of other SWAT output parameters can give an indication of the daily climate and conditions for growth and illuminate the divergent results exhibited in Figure 30. Evapotranspiration (ET) rates are dependent on the net available energy needed for water to evaporate, among others, the amount of which may be reduced due to cloud cover. A visual comparison of daily ET provides a convincing case that cloud cover, as well as other factors such as temperature and humidity, differs considerably between HRU 211 and the other two HRU examples, in particular between Julien day 25 and 85 (Figure 31). The ET pattern also echoes the plant development curves of Figure 30. In fact, simulated biomass is highly correlated (r^2 = 0.97) with simulated ET, suggesting that differences in simulated biomass values may be due to simulated climatic variations. Because ET was modeled (see Section 4.2), it is also plausible to assume that some of the error of the SWAT plant growth model is due to differences in simulated and observed climatic conditions.

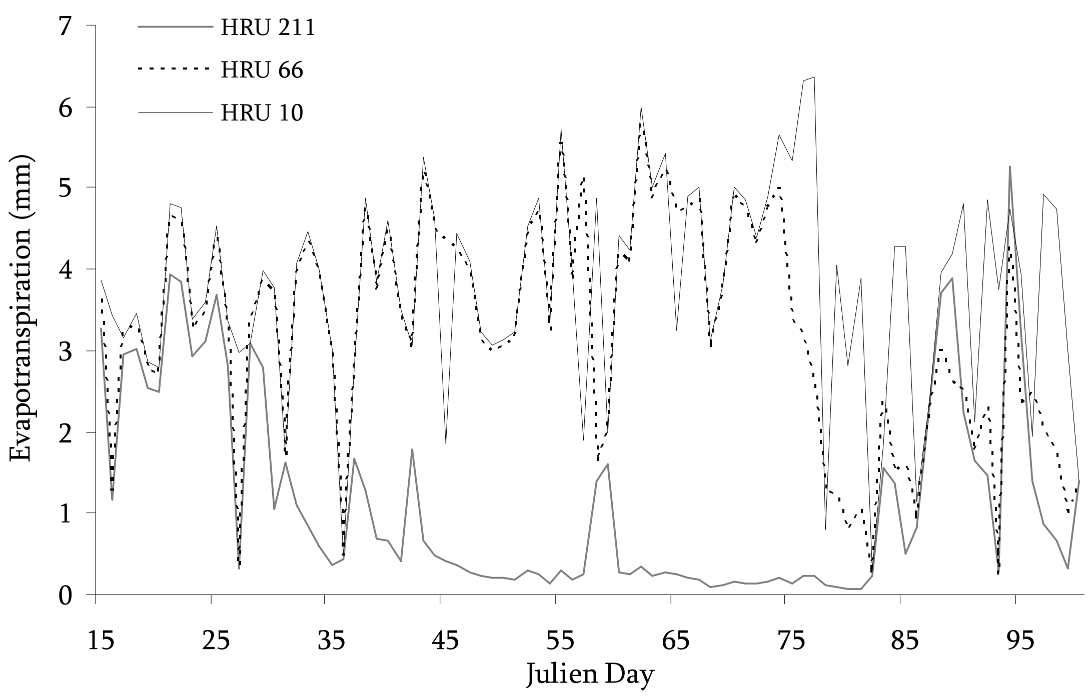

Figure 31: Simulated evapotranspiration for HRU 211 and HRU 66.

iv. Challenges and Prospects for Pineapple Crop Growth Simulations with SWAT

There are many other possible explanations for the inaccuracy of SWAT simulated plant growth (Figure 29). Identifying which factors contribute to this error is beyond the scope of this study, accordingly the evaluation hereinafter is only speculative. Ideally, a crop growth model is constructed with locally sampled data used to calculate actual crop parameters such as LAI and radiation-use efficiency. All data required to run the SWAT crop growth model was obtained from a review of the literature. The data, therefore, is sourced from several geographic regions, including Mexico, Australia, Brazil, and Hawaii (Appendix I, Table 4). While data obtained from the literature is the best available, using local data would likely increase the accuracy of the model.

Most probably the range of observed biomass is more dispersed than simulated biomass (Figure 29) because factors that appreciably affect growth *in situ*, such as nutrient availability, soil type, water availability, etc., are not modeled by SWAT. Also of principle importance is SWAT's inability to simulate crop growth over a two calendar year period, which is elaborated upon in the following section. These two examples demonstrate how the growing conditions of the observed biomass could not be recreated for SWAT simulations due to the limited SWAT model framework, calling for a more complex and comprehensive model to adequately simulate pineapple growth.

Challenges: simulating crop growth over a two calendar-year period

The SWAT model was developed for use in the northern hemisphere which, as detailed below, restricts the model's ability to simulate plant growth over a two calendar-year period. In general, occidental crops are planted in the spring and harvested in the fall; the entire crop cycle, therefore, falls within a single calendar-year. The crop cycles of many tropical crops, such as sugarcane and pineapple, are longer than a year and may be as long as three years if ratoon crops are harvested. Often, tropical crops are also planted at the beginning of the rainy season (April or May in Panama) and not harvested until the beginning of the following calendar-year, during the dry season.

In SWAT, management operations must be synchronized according to the calendar-year, starting in January and ending in December and all crops must be harvested by the end of a calendar-year. If this is not written into the management scenario, a default harvest and kill operation will be performed and the crop will not be replaced. There exists some discussion in the SWAT-user community on this subject matter (SWAT forum, 2007) and there is speculation that the SWAT developers will modify the program code in order to remove the automatic harvest and kill operation. In any case, this represents a significant caveat for SWAT model application in the tropics.

SWAT does provide the user with limited control over how a crop grows, allowing for some flexibility to work around, although not remediate, this caveat. In SWAT management scenarios, the number of heat units needed to bring a plant to maturity can be user-defined for different crops and for different years, allowing the user to manipulate – speed up or slow down – plant development over the simulation period. For example, consider a crop which normally requires 3000 heat units and about 150 days to reach maturity. Changing the number of heat units needed to bring this plant to maturity to 20 would allow SWAT to simulate plant maturation in only a day or two, depending on climatic conditions. Taking advantage of the user-defined heat units, pineapple crop cover was able to be simulated over a two calendar-year period (necessary for sediment and flow calibration). On December 31 of each calendar-year a harvest and kill operation was written into the management scenario, even though most pineapple crops would not have reached maturity (in TCH, fruits are harvested on average 372 days after planting). On the following day, January 1 of the subsequent year, a planting operation was written into the management scenario. For this operation, the heat units need to bring the pineapple plant to maturity were set at 30, allowing the plant to reach maturity within a few days.

Clearly, creating management scenarios with such complexity is an arduous, non user-friendly process and introduces extensive uncertainty and error into growth simulations. This will most certainly also impact sediment and flow predictions. Any future application of SWAT to pineapple-related research should focus efforts on modifying the program code that controls management scenarios in order to eliminate the mandatory harvest and kill operation at the end of each calendar-year.

Future Prospects: the ALOHA-pineapple/SWAT model duo

While amending the SWAT program code could remedy the management scenario problem, data used in the pineapple growth model also needs to be further refined and the model must be validated to improve growth simulations. Rather than working within the SWAT framework, SWAT could be linked to the ALOHA-pineapple model (Zhang and Bartholomew, 1993), a CERES (Crop Environment REsource Synthesis) based crop growth simulation program. The ALOHA program was developed by researchers at the University of Hawaii and has successfully simulated the effects of environmental factors and land management practices on pineapple growth and crop yield in Hawaii, Australia, and Cote D'Ivoire (Zhang and Bartholomew, 1993, Zhang et al., 1997).

An unresolved issue is whether it would be more cost and time effective to modify the simulation procedure of SWAT to reflect the physiology of pineapple or to modify SWAT to accept the output of ALOHA Pineapple. The following discussion highlights the differences between the two models, a first step in the process of deciding how best to proceed in any effort to modify SWAT for use in estimating sediment yield from lands planted to pineapple.

The general approaches taken by the SWAT and ALOHA models to simulate growth are similar, but there are also some important differences. The similarities include the simulation of leaf-area development, light interception, and biomass accumulation as modeled by equations 1 – 3, although ALOHA has other important modifications. For example, while the total potential biomass accumulation in SWAT is assumed to contribute, unrestrained, to plant growth[16], ALOHA uses four parameters to account for the effects of inter-plant competition: temperature, drought stress, nitrogen deficiency, and plant density factors. These parameters are used to calculate the actual biomass accumulation on a given day from the maximum potential biomass accumulation (Equation 3).

To ensure accurate plant growth simulation, ALOHA considers the differences in growth of planting material due to weight and type (slip, crown, or sucker). In practice, all planting materials appear to have similar leaf areas (Bartholomew et al., 2003), however, heavier planting material grows more rapidly and crowns produce more roots than suckers (Py et al., 1987). SWAT can consider the initial LAI of the planting material but assumes growth will continue along the optimal growth curve from thereinafter. In contrast, ALOHA incorporates a subroutine that divides plant growth into seven phenological stages to allow for better prediction of plant growth rates before and during such stages. This allows the model to consider the differences in growth of the plant at the various stages, for example, the arrest of leaf-area development after induction or reproductive development and allocation of biomass to fruit development thereinafter.

A vital factor in erosion modeling is the accurate simulation of canopy cover and root development. ALOHA partitions biomass into individual plant components (leaves, roots, fruit, crown, etc.) and models this process according to phenological stage. The only biomass partitioning that SWAT considers is in root development, assuming that biomass allocated to roots varies from 40% at emergence to 20% at maturity. In pineapple, roots do not appear to comprise more than 10% of the biomass at any time. Root development, however, is not only a function of the growth cycle but is also dependent soil temperature, which ALOHA considers via the temperature effects of plant density.

Partitioning of biomass, as ALOHA does, is likely better able to reflect crop yields than SWAT. A single ratio of harvested to total dry biomass, or the harvest efficiency ratio

[16] Actually, SWAT can model the effects of increased atmospheric carbon dioxide concentrations on radiation-use efficiency and, thus, on biomass accumulation.

(HVSTI parameter; Appendix I, Table 4), is used by SWAT to calculate harvest yield. The harvest ratio in TCH was calculated to be, on average, 0.36 while harvest ratios range from 0.22 to 0.46. Fruit weight at harvest is dependent on multiple environmental factors, such as planting density, nutrient availability, drought stress, temperature, etc., and their effects on fruit weight are not always proportional to their effects on plant weight, or total plant biomass production (Malezieux, 1993, Zhu et al., 1997). Indeed, this trend is exhibited in TCH were total plant biomass is not correlated ($r^2 = 0.09$) with fruit weight. Since ALOHA is able to partition biomass to each part of the plant, it is likely better able to consider the effects environmental factors can have on fruit harvest. Conversely, SWAT, with only a single inflexible harvest ratio, cannot model these effects. It is for this reason that the evaluation of the SWAT growth model considered only total plant biomass and not crop yield (Figure 29).

Environmental factors affect both plant development and crop yield, thus simulating plant response to a changing environment will also be essential to support flow and erosion modeling in the TCH basins. Unlike SWAT, ALOHA includes factors to account for the effects of drought stress, nitrogen deficiency, and temperature on plant growth. ALOHA also is able to model the effects of resource competition and planting density on biomass accumulation. High planting densities, such as those observed in TCH, - on average 60,000 plants/ha (IDIAP, 2007, Martez and Vergara, 2004) - increase the number of heat-units required for plants to reach a particular phenological phase (Zhang, 1992). This is because increased canopy cover will, presumably, result in a reduction in the heat transported to the meristem (the point of growth) which will thus reduce leaf appearance (Zhang, 1992). ALOHA calculates a plant competition factor from the planting density (LAI) and reduces the time between elongation of successive leaves, or phyllochron, accordingly (Zhang, 1992). SWAT does not account for competition and considers that all plants within a delimited parcel of land (the HRU) react homogenously and that plant growth and resource availability, such as light and water, are limited only by climate conditions.

The ALOHA model clearly employs a sophistication far superior to that currently available in SWAT. Although it is only speculative, ALOHA does appear to be a better prospect for pineapple growth simulations than the SWAT growth model, as is. Some of the attributes of ALOHA discussed above could probably be incorporated into the SWAT crop growth model and may enhance simulated predictions. Because much of the input and output data are comparable for both models, a link between the two models would be possible but would require a substantial modification of the program coding, yet it could prove to be very useful for this and other studies. It would be this combination of programs that is likely the best suited for the needs of the TCH basins.

Appendix III: Uncertainty Figures

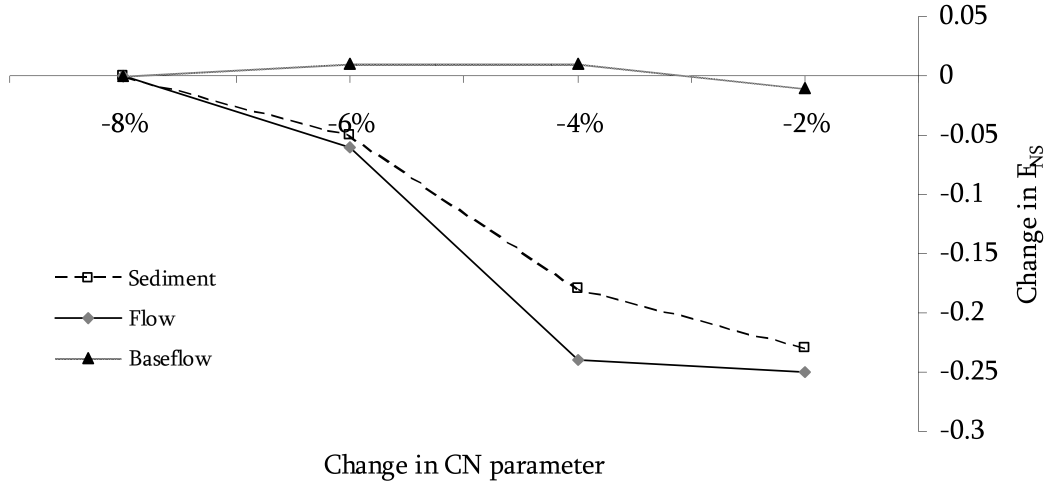

Figure 32: Uncertainty of CN parameter

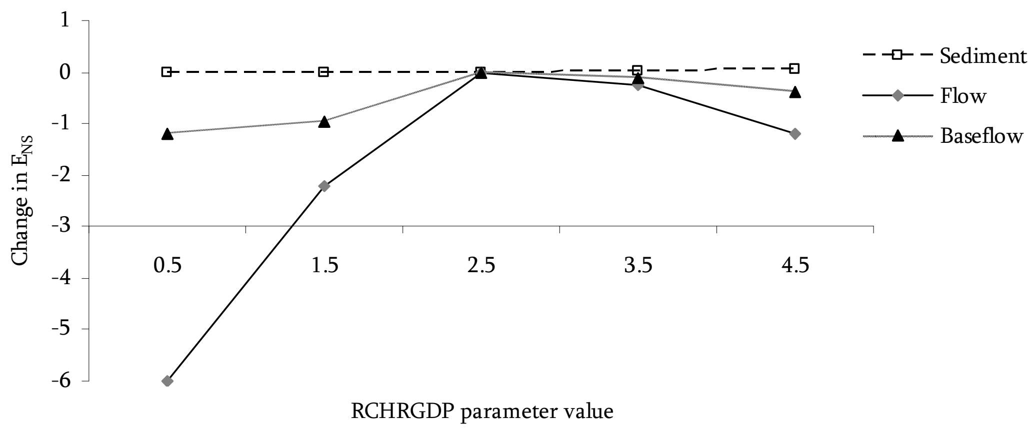

Figure 33: Uncertainty of RCHRGDP parameter

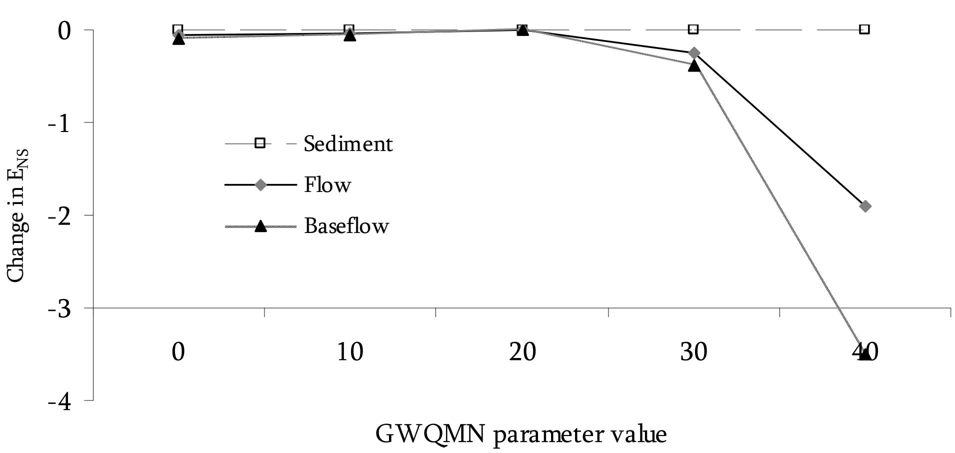

Figure 34: Uncertainty of GWQMN parameter

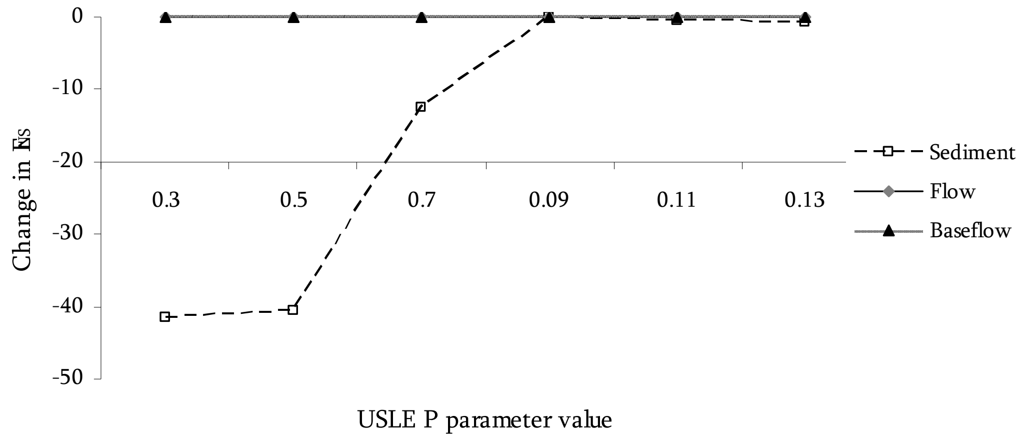

Figure 35: Uncertainty of USLE P parameter

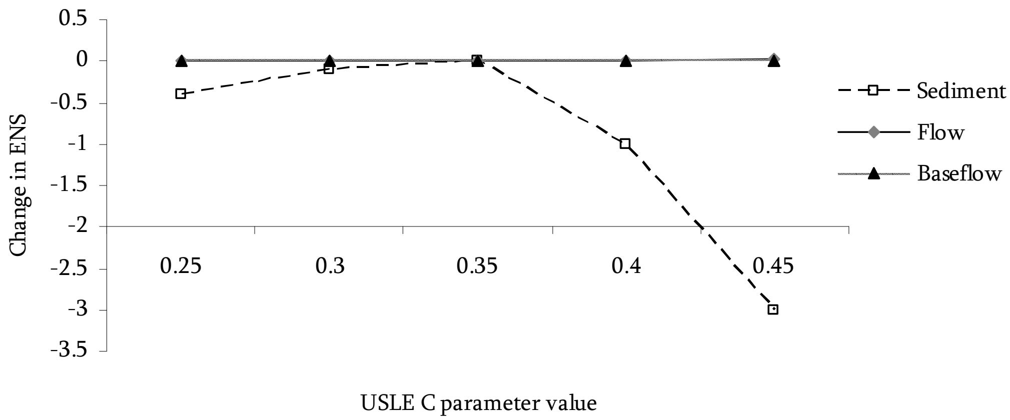

Figure 36: Uncertainty of USLE C parameter

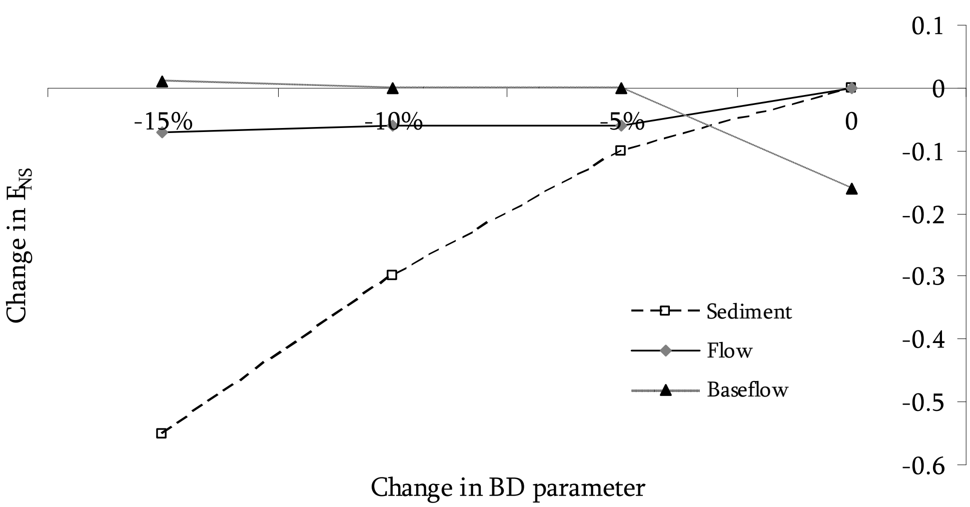

Figure 37: Uncertainty of BD parameter

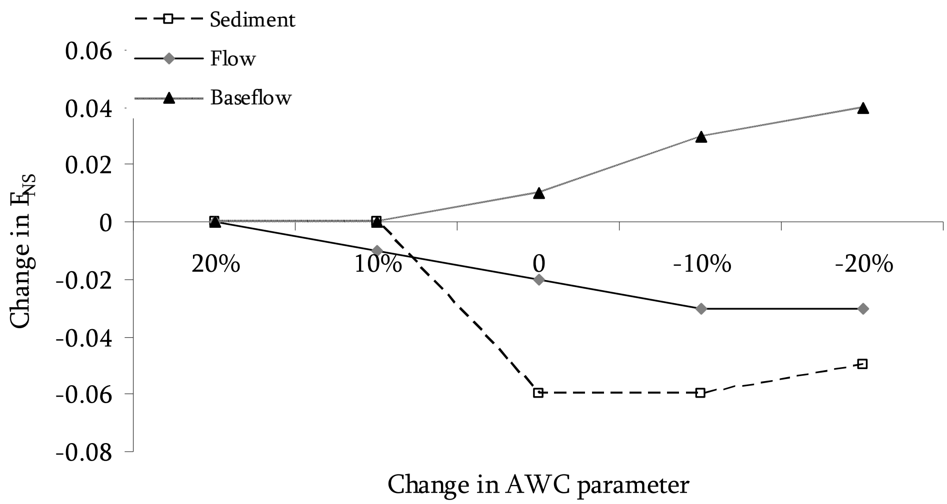

Figure 38: Uncertainty of the AWC parameter

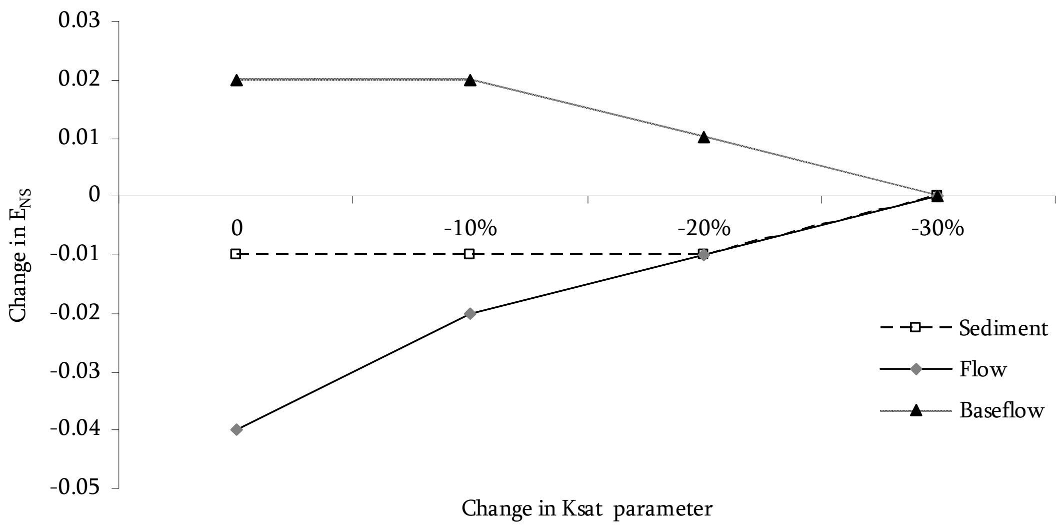

Figure 39: Uncertainty of the K_{sat} parameter.

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