HESS-2015 -538, 31 Jan 2017

Flood risk reduction and flow buffering as ecosystem services: I. Theory on flow persistence, flashiness and base flow

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Abstract

Flood damage reflects insufficient adaptation of human presence and activity to location and variability of river flow in a given climate. Flood risk increases when landscapes degrade, counteracted or aggravated by engineering solutions. Efforts to maintain and restore buffering as ecosystem function may help adaptation to climate change, but require quantification of effectiveness in their specific social-ecological context. However, the specific role of forests, trees, soil and drainage pathways in flow buffering, given geology, land form and climate, remains controversial. Complementing the scarce heavily instrumented catchments with reliable long-term data, especially in the tropics, there is a need for metrics for data-sparse conditions. We present and discuss a flow persistence metric that relates transmission to river flow of peak rainfall events, to the base flow component of the water balance. The dimensionless flow persistence parameter F_p is defined in a recursive flow model and can be estimated from limited time series of observed daily flow, without requiring knowledge of spatially distributed rainfall upstream. The F_p metric (or its change over time from what appears to be the local norm) matches local knowledge concepts. Inter-annual variation in the F_p metric in sample watersheds correlates with variation in the 'flashiness index' used in existing watershed health monitoring programs, but the relationship between these metrics varies with context. Inter-annual variation in F_p also correlates with common base-flow indicators, but again in a way that varies between watersheds. Further exploration of the responsiveness of F_p in watersheds with different characteristics to the interaction of land cover and the specific realization of space-time patterns of rainfall in a limited observation period is needed to evaluate interpretation of F_p as indicator of anthropogenic changes in watershed condition.

1 Introduction

Floods can be the direct result of reservoir dams, log jams or protective dykes breaking, with water derived from unexpected heavy rainfall, rapid snow melt, tsunamis or coastal storm surges. We focus here on floods that are associated, at least in the public eye, with watershed degradation. Degradation of watersheds and its consequences for river flow regime and flooding intensity and frequency are a widespread concern (Brauman et al., 2007; Bishop and Pagiola, 2012; Winsemius et al., 2013). Engineering measures (dams, reservoirs, canalization, dykes, and flow regulation) can significantly alter the flow regime of rivers, and reduce the direct relationship with landscape conditions in the (upper) catchment (Poff et al., 1997). The life expectancy of such structures depends, however, on the sediment load of incoming rivers and thus on upper watershed conditions (Graf et al., 2010). Where ‘flow regulation’ has been included in efforts to assess an economic value of ecosystem services, it can emerge as a major component of overall value; the economic damage of floods to cities build on floodplains can be huge and the benefits of avoiding disasters thus large (Farber et al., 2002; Turner and Daily, 2002; Brauman et al., 2007). The ‘counterfactual’ part of any avoided damage argument, however, depends on metrics that are transparent in their basic concept and relationship with observables. Basic requirements for a metric to be used in managing issues of public concern in a complex multistakeholder environment are that it i) has a direct relationship with a problem that needs to be solved (‘salience’), ii) is aligned with current science-based understanding of how the underpinning systems function and can be managed (‘credibility’) and iii) can be understood from local and public/policy perspectives (‘legitimacy’) (Clark et al. 2011). Figure 1 summarizes these requirements, building on van Noordwijk et al. (2016).

⇨ Figure 1

In the popular discussion on floods, especially in the tropics, a direct relationship with deforestation and reforestation is still commonly perceived to dominate, and forest cover is seen as salient and legitimate metric of watershed quality (or of urgency of restoration where it is low). A requirement for 30% forest cover, is for example included in the spatial planning law in Indonesia in this context (Galudra and Sirait, 2009). Yet, rivers are probably dominated by the other 70% of the landscape. There is a problem with the credibility of assumed deforestation-flood relations (van Noordwijk et al., 2007; Verbist et al., 2010), beyond the local scales (< 10 km^2) of paired catchments where ample direct empirical proof exists, especially in non-tropical climate zones (Bruijnzeel, 1990, 2004). Current watershed rehabilitation programs that focus on increasing tree cover in upper watersheds are only partly aligned with current scientific evidence of effects of large-scale tree planting on streamflow (Ghimire et al., 2014; Malmer et al., 2010; Palmer, 2009; van Noordwijk et al., 2015a). The relationship between floods and change in forest quality and quantity, and the availability of evidence for such a relationship at various scales has been widely discussed over the past decades (Andréassian, 2004; Bruijnzeel, 2004; Bradshaw et al., 2007; van Dijk et al., 2009). Measurements in Cote d’Ivoire, for example, showed strong scale dependence of runoff from 30-50% of rainfall at 1 m^2 point scale, to 4% at 130 ha watershed scale, linked to spatial variability of soil properties plus variations in rainfall patterns (Van de Giesen et al., 2000). The ratio between peak and average flow decreases from headwater streams to main rivers in a predictable manner; while mean annual discharge scales with $(area)^{1.0}$, maximum river flow was found to scale with $(area)^{0.4}$ to $(area)^{0.7}$ on average (Rodríguez-Iturbe and Rinaldo, 2001; van Noordwijk et al., 1998; Herschy, 2002), with even lower powers for area in flash floods that are linked to an extreme rainfall event over a restricted area (Marchi et al., 2010). The determinants of peak flow are thus scale-dependent, with space-time correlations in rainfall interacting with subcatchment-level flow buffering at any point along the river. Whether and where peak flows lead to flooding depends on the capacity of the rivers to pass on peak flows towards downstream lakes or the sea, assisted by riparian buffer areas with sufficient storage capacity (Baldasarre et al., 2013). Reducing local flooding risk by increased drainage increases flooding risk downstream, challenging the nested-scales management of watersheds to find an optimal spatial distribution, rather than minimization, of flooding probabilities. Well-studied effects of forest conversion on peak flows in small upper stream catchments (Bruijnzeel, 2004; Alila et al., 2009) do not necessarily translate to flooding downstream. With most of the published studies still referring to the temperate zone, the situation in the tropics (generally in the absence of snow) is contested (Bonell and Bruijnzeel, 2005). As summarized by Beck et al. (2013) meso- to macroscale catchment studies (>1 and >10 000 km^2, respectively) in the tropics, subtropics, and warm temperate regions have mostly failed to demonstrate a clear relationship between river flow and change in forest area. Lack of evidence cannot be firmly interpreted as evidence for lack of effect, however. Detectability of effects depends on their relative size, the accuracy of the measurement devices, length of observation period, and background variability of the signal. A recent econometric study for Peninsular Malaysia by Tan-Soo et al. (2014) concluded that, after appropriate corrections for space-time correlates in the data-set for 31 meso- and macroscale basins (554-28,643 km^2), conversion of inland rain forest to monocultural plantations of oil palm or rubber increased the number of flooding days reported, but not the number of flood events, while conversion of wetland forests to urban areas reduced downstream flood duration. This Malaysian study may be the first credible empirical evidence at this scale. The difference between results for flood duration and flood frequency and the result for draining wetland forests warrant further scrutiny. Consistency of these findings with river flow models based on a water balance and likely pathways of water under the influence of change in land cover and land use has yet to be shown. Two recent studies for Southern China confirm the conventional perspective that deforestation increases high flows, but are contrasting in effects of Reforestation. Zhou et al. (2010) analysed a 50-year data set for Guangdong Province in China and concluded that forest recovery had not changed the annual water yield (or its underpinning water balance terms precipitation and evapotranspiration), but had a statistically significant positive effect on dry season (low) flows. Liu et al. (2015), however, found for the Meijiang watershed (6983 km^2) in subtropical China that while historical deforestation had decreased the magnitudes of low flows (daily flows $\leqq$ Q95%) by 30.1%, low flows were not significantly improved by Reforestation. They concluded that recovery of low flows by Reforestation may take much longer time than expected probably because of severe soil erosion and resultant loss of soil infiltration capacity after deforestation. Changes in river flow patterns over a limited period of time can be the combined and interactive effects of variations in the local rainfall regime, land cover effects on soil structure and engineering modifications of water flow that can be teased apart with modelling tools (Ma et al., 2014).

Lacombe et al. (2015) documented that the hydrological effects of natural regeneration differ from those of plantation forestry, while forest statistics do not normally differentiate between these different land covers. In a regression study of the high and low flow regimes in the Volta and Mekong river basins Lacombe and McCartney (2016) found that in the variation among tributaries various aspects of land cover and land cover change had explanatory power. Between the two basins, however, these aspects differed. In the Mekong basin variation in forest cover had no direct effect on flows, but extending paddy areas resulted in a decrease in downstream low flows, probably by increasing evapotranspiration in the dry season. In the Volta River Basin, the conversion of forests to crops (or a reduction of tree cover in the existing parkland system) induced greater downstream flood flows. This observation is aligned with the experimental identification of an optimal, intermediate tree cover from the perspective of groundwater recharge in parklands in Burkina Faso (Ilstedt et al., 2016).

The statistical challenges of attribution of cause and effect in such data-sets are considerable with land use/land cover effects interacting with spatially and temporally variable rainfall, geological configuration and the fact that land use is not changing in random fashion or following any pre-randomized design (Alila et al., 2009; Rudel et al., 2005). Hydrological analysis across 12 catchments in Puerto Rico by Beck et al. (2013) did not find significant relationships between the change in forest cover or urban area, and change in various flow characteristics, despite indications that regrowing forests increased evapotranspiration.

These observations imply that percent tree cover (or other forest related indicators) is probably not a good metric for judging the ecosystem services provided by a watershed (of different levels of 'health'), and that a metric more directly reflecting changes in river flow may be needed. Here we will explore a simple recursive model of river flow (van Noordwijk et al., 2011) that (i) is focused on (loss of) flow predictability, (ii) can account for the types of results obtained by the cited recent Malaysian study (Tan-Soo et al., 2014), and (iii) may constitute a suitable performance indicator to monitor watershed 'health' through time.

Before discussing the credibility dimension of river flow metrics, the way these relate to the salience and legitimacy issues around 'flood damage' as policy issue need attention. The salient issue of 'flood damage' is compatible with a common dissection of risk as the product of exposure, hazard and vulnerability (steps 1, 2 and 3 in Figure 2). Many aspects beyond forests and tree cover play a role; in fact these factors are multiple steps away (step 7A) from the direct river flow dynamics that determine floods. Extreme discharge events plus river-level engineering (steps 4 and 5) co-determine hazard (step 2), while exposure (step 1) depends on topographic position interacting with human presence, and vulnerability can be modified by engineering at a finer scale and be further reduced by advice to leave an area in high-risk periods. A recent study (Jongman et al., 2015) found that human fatalities and material losses between 1980 and 2010 expressed as a share of the exposed population and gross domestic product were decreasing with rising income. The planning needed to avoid extensive damage requires quantification of the risk of higher than usual discharges, especially at the upper tail end of the flow frequency distribution.

⇨ Figure 2

The statistical scarcity, per definition, of 'extreme events' and the challenge of data collection where they do occur, make it hard to rely on site-specific empirical data as such. Inference of risks needs some trust in extrapolation methods, as is often provided by use of trusted underlying mechanisms and/or data obtained in a geographical proximity. Existing data on flood frequency and duration, as well as human and economic damage are influenced by topography, soils, human population density and economic activity, responding to engineered infrastructure (step 5 in Figure 2), as well as the extreme rainfall events that are their proximate cause (step 6). Subsidence due to groundwater extraction in urban areas of high population density is a specific problem for a number of cities built on floodplains (such as Jakarta and Bangkok), but subsidence of drained peat areas has also been found to increase flooding risks elsewhere (Sumarga et al., 2016). Common hydrological analysis of flood frequency (called 1 in 10-, 1 in 100-, 1 in 1000-year flood events, for example) relies on direct observations at step 4 in Fig. 2, but typically requires spatial extrapolation beyond points of data collection through river flow models that combine at least steps 5 and 6. Relatively simple ways of including the conditions in the watershed (step 7) in such models rely on the runoff curve number method (Ponce et al., 1996) and the SWAT (Soil water assessment tool) model that was built on its foundation (Gassman et al. 2007). Applications on tropical soils have had mixed success (Oliveira et al. 2016). Describing peak flows as a proportion of the rainfall event that triggered them has a long history, but where the proportionality factors are estimated for ungauged catchments results may be unreliable (Efstratoiadis et al., 2014). More refined descriptions of the infiltration process (step 7B) are available, using recursive models as filters on empirical data (Grimaldi et al., 2013), but data for this approach may not be generally available. According to van den Putte et al. (2013) the Green–Ampt infiltration equation can be fitted to data for dry conditions when soil crusts limit infiltration, but not in wet winter conditions. These authors argued that simpler models may be better.

Analysis of likely change in flood frequencies in the context of climate change adaptation has been challenging (Milly et al., 2002; Ma et al., 2014). There is a lack of simple performance indicators for watershed health at its point of relating precipitation P and river flow Q (step 4 in Figure 2) that align with local observations of river behaviour and concerns about its change and that can reconcile local, public/policy and scientific knowledge, thereby helping negotiated change in watershed management (Leimona et al., 2015). The behaviour of rivers depends on many climatic (step 6 in Figure 2) and terrain factors (step 7A-D in Figure 2) that make it a challenge to differentiate between human induced ecosystem structural change and soil degradation (step 7B) on one hand and intrinsic variability on the other. Step 8 in Figure 2 represents the direct influence of climate on vegetation, but also a possible reverse influence (van Noordwijk et al., 2015b). Hydrological models tend to focus on predicting hydrographs at one or more temporal scales, and are usually tested on data-sets from limited locations. Despite many decades (if not centuries) of hydrological modelling, current hydrologic theory, models and empirical methods have been found to be largely inadequate for sound predictions in ungauged basins (Hrachowitz et al., 2013). Efforts to resolve this through harmonization of modelling strategies have so far failed. Existing models differ in the number of explanatory variables and parameters they use, but are generally dependent on empirical data of rainfall that are available for specific measurement points but not at the spatial resolution that is required for a close match between measured and modelled river flow. Spatially explicit models have conceptual appeal (Ma et al., 2010) but have too many degrees of freedom and too many opportunities for getting right answers for wrong reasons if used for empirical calibration (Beven, 2011). Parsimonious, parameter-sparse models are appropriate for the level of evidence available to constrain them, but these parameters are themselves implicitly influenced by many aspects of existing and changing features of the watershed, making it hard to use such models for scenario studies of changing land use and change in climate forcing. Here we present a more direct approach deriving a metric of flow predictability that can bridge local concerns and concepts to quantified hydrologic function: the 'flow persistence' parameter as directly observable characteristic (step 4 in Figure 2), that can be logically linked to the primary points of intervention in watershed management, interacting with climate and engineering-based change.

In this contribution to the debate we will first define the metric 'flow persistence' in the context of temporal autocorrelation of river flow and then derive a way to estimate its numerical value. In part II we will apply the algorithm to river flow data for a number of contrasting meso-scale watersheds. In the discussion of this paper we will consider the new flow persistence metric in terms of three groups of criteria for usable knowledge (Fig. 1; Clark et al., 2011; Lusiana et al., 2011; Leimona et al., 2015) based on salience (I,II), credibility (III, IV) and legitimacy (V-VII):

I. Does flow persistence relate to important aspects of watershed behaviour, complementing existing metrics such as the 'flashiness index' and 'base flow separation' techniques?

II. Does its quantification help to select management actions?

III. Is there consistency of numerical results?

IV. How sensitive is it to bias and random error in data sources?

V. Does it match local knowledge?

VI. Can it be used to empower local stakeholders of watershed management?

VII. Can it inform local risk management?

2 Flow persistence in water balance equations

2.1 Recursive model

One of the easiest-to-observe aspects of a river is its day-to-day fluctuation in water level, related to the volumetric flow (discharge) via rating curves (Maidment, 1992). Without knowing details of upstream rainfall and the pathways the rain takes to reach the river, observation of the daily fluctuations in water level allows important inferences to be made. It is also of direct utility: sudden rises can lead to floods without sufficient warning, while rapid decline makes water utilization difficult. Indeed, a common local description of watershed degradation is that rivers become more 'flashy' and less predictable, having lost a buffer or 'sponge' effect (Joshi et al., 2004; Ranieri et al., 2004; Rahayu et al., 2013). A simple model of river flow at time t, Q_t, is that it is similar to that of the day before (Q_{t-1}), multiplied with F_p, a dimensionless parameter called 'flow persistence' (van Noordwijk et al., 2011) plus an additional stochastic term $Q_{a,t}$:

$$Q_t = F_p Q_{t-1} + Q_{a,t} \qquad [1].$$

Q_t is for this analysis expressed in mm d^{-1}, which means that measurements in $m^3 s^{-1}$ need to be divided by the relevant catchment area, with appropriate unit conversion. If river flow were constant, it would be perfectly predictable, i.e. F_p would be 1.0 and $Q_{a,t}$ zero; in contrast, an F_p-value equal to zero and $Q_{a,t}$ directly reflecting erratic rainfall represents the lowest possible level of predictability.

The F_p parameter is conceptually identical to the 'recession constant' commonly used in hydrological models, typically assessed during an extended dry period when the $Q_{a,t}$ term is negligible and streamflow consists of base flow only (Tallaksen, 1995); empirical deviations from a straight line in a plot of the logarithm of Q against time are common and point to multiple rather than a single groundwater pool that contributes to base flow. The larger catchment area has a possibility to get additional flow from multiple independent groundwater contribution.

As we will demonstrate in a next section, it is possible to derive F_p even when $Q_{a,t}$ is not negligible. In climates without distinct dry season this is essential; elsewhere it allows a comparison of apparent F_p between wet and dry parts of the hydrologic year. A possible interpretation, to be further explored, is that decrease over the years of F_p indicates 'watershed degradation' (i.e. greater contrast between high and low flows), and an increase 'improvement' or 'rehabilitation' (i.e. more stable flows).

If we consider the sum of river flow over a period of time (from 1 to T) we obtain

$$\Sigma_1^T Q_t = F_p \Sigma_1^T Q_{t-1} + \Sigma_1^T Q_{a,t} \qquad [2].$$

If the period is sufficiently long period for Q_T minus Q_0 (the values of Q_t for t=T and t=0, respectively) to be negligibly small relative to the sum over all t's, we may equate $\Sigma_1^T Q_t$ with $\Sigma_1^T Q_{t-1}$ and obtain a first way of estimating the F_p value:

$$F_p = 1 - \Sigma_1^T Q_{a,t} / \Sigma_1^T Q_t \qquad [3].$$

The stochastic $Q_{a,t}$ can be interpreted in terms of what hydrologists call 'effective rainfall' (i.e. rainfall minus on-site evapotranspiration, assessed over a preceding time period tx since previous rain event):

$$Q_t = F_p Q_{t-1} + (1-F_p)(P_{tx} - E_{tx}) \qquad [4].$$

Where P_{tx} is the (spatially weighted) precipitation on day t (or preceding precipitation released as snowmelt on day t) in mm d^{-1}; E_{tx}, also in mm d^{-1}, is the preceding evapotranspiration that allowed for infiltration during this rainfall event (*i.e.* evapotranspiration since the previous soil-replenishing rainfall that induced empty pore space in the soil for infiltration and retention), or replenishment of a water film on aboveground biomass that will subsequently evaporate. More complex attributions are possible, aligning with the groundwater replenishing bypass flow and the water isotopic fractionation involved in evaporation (Evaristo et al., 2015).

The consistency of multiplying effective rainfall with $(1-F_p)$ can be checked by considering the geometric series $(1-F_p)$, $(1-F_p) F_p$, $(1-F_p) F_p^2$, …, $(1-F_p) F_p^n$ which adds up to $(1-F_p)(1 - F_p^n)/(1-F_p)$ or $1 - F_p^n$. This approaches 1 for large n, suggesting that all of the water attributed to time t, *i.e.* $P_t - E_{tx}$, will eventually emerge as river flow. For $F_p = 0$ all of $(P_t - E_{tx})$ emerges on the first day, and river flow is as unpredictable as precipitation itself. For $F_p = 1$ all of $(P_t - E_{tx})$ contributes to the stable daily flow rate, and it takes an infinitely long period of time for the last drop of water to get to the river. For declining F_p, $(1 > F_p > 0)$, river flow gradually becomes less predictable, because a greater part of the stochastic precipitation term contributes to variable rather than evened-out river flow.

Taking long term summations of the right- and left- hand sides of Eq.(4) we obtain:

$$\Sigma Q_t = \Sigma(F_p Q_{t-1} + (1-F_p)(P_t - E_{tx})) = F_p \Sigma Q_{t-1} + (1-F_p)(\Sigma P_t - \Sigma E_{tx}) \qquad [5].$$

Which is consistent with the basic water budget, $\Sigma Q = \Sigma P - \Sigma E$, at time scales long enough for changes in soil water buffer stocks to be ignored. As such the total annual, and hence the mean daily river flow are independent of F_p. This does not preclude that processes of watershed degradation or restoration that affect the partitioning of P over Q and E also affect F_p.

2.2 Base flow

Clarifying the $Q_{a,t}$ contribution is equivalent with one of several ways to separate base flow from peak flows. Rearranging Eq.(3) we obtain

$$\Sigma_1^T Q_{a,t} = (1 - F_p) \Sigma_1^T Q_t \qquad [6].$$

The $\Sigma Q_{a,t}$ term reflects the sum of peak flows in mm. Its complement, $F_p \Sigma Q_t$, reflects the sum of base flow, also in mm. For $F_p = 1$ (the theoretical maximum) we conclude that all $Q_{a,t}$ must be zero, and all flow is 'base flow'.

2.3 Low flows

The lowest flow expected in an annual cycle is $Q_x F_p^{Nmax}$ where Q_x is flow on the first day without rain and N_{max} the longest series of dry days. Taken at face value, a decrease in F_p has a strong effect on low-flows, with a flow of 10% of Q_x reached after 45, 22, 14, 10, 8 and 6 days for F_p = 0.95, 0.9, 0.85, 0.8, 0.75 and 0.7, respectively. However, the groundwater reservoir that is drained, equalling the cumulative dry season flow if the dry period is sufficiently long, is $Q_x/(1-F_p)$. If F_p decreases to F_{px} but the groundwater reservoir ($Res = Q_x/(1-F_p)$) is not affected, initial flows in the dry period will be higher ($Q_x F_{px}^i (1-F_{px})\ Res > Q_x F_p^i (1-F_p)\ Res$ for $i < \log((1-F_{px})/(1-F_p))/\log(F_p/F_{px})$). It thus matters how low flows are evaluated: from the perspective of the lowest level reached, or as cumulative flow. The combination of climate, geology and land form are the primary determinants of cumulative low flows, but if land cover reduces the recharge of groundwater there may be impacts on dry season flow, that are not directly reflected in F_p.

If a single F_p value would account for both dry and wet season, the effects of changing F_p on low flows may well be more pronounced than those on flood risk. Empirical tests are needed of the dependence of F_p on Q (see below). Analysis of the way an aggregate F_p depends on the dominant flow pathways provides a basis for differentiating F_p within a hydrologic year.

2.4 Flow-pathway dependence of flow persistence

The patch-level partitioning of water between infiltration and overland flow is further modified at hillslope level, with a common distinction between three pathways that reach streams: overland flow, interflow and groundwater flow (Band et al., 1993; Weiler and McDonnell, 2004). An additional interpretation of Eq.(1), potentially adding to our understanding of results but not needed for analysis of empirical data, can be that three pathways of water through a landscape contribute to river flow (Barnes, 1939): groundwater release with $F_{p,g}$ values close to 1.0, overland flow with $F_{p,o}$ values close to 0, and interflow with intermediate $F_{p,i}$ values.

$$Q_t = F_{p,g}\, Q_{t-1,g} + F_{p,i}\, Q_{t-1,i} + F_{p,o}\, Q_{t-1,o} + Q_{a,t} \quad [7],$$

$$F_p = (F_{p,g}\, Q_{t-1,g} + F_{p,i}\, Q_{t-1,i} + F_{p,o}\, Q_{t-1,o})/Q_{t-1} \quad [8].$$

On this basis a decline or increase in overall weighted average F_p can be interpreted as indicator of a shift of dominant runoff pathways through time within the watershed. Dry season flows are dominated by $F_{p,g}$. The effective F_p in the rainy season can be interpreted as indicating the relative importance of the other two flow pathways. F_p reflects the fractions of total river flow that are based on groundwater, overland flow and interflow pathways:

$$F_p = F_{p,g}\, (\Sigma Q_{t,g} / \Sigma Q_t) + F_{p,o}\, (\Sigma Q_{t,o} / \Sigma Q_t) + F_{p,i}\, (\Sigma Q_{t,i} / \Sigma Q_t) \quad [9].$$

Beyond the type of degradation of the watershed that, mostly through soil compaction, leads to enhanced infiltration-excess (or Hortonian) overland flow (Delfs et al., 2009), saturated conditions throughout the soil profile may also induce overland flow, especially near valley bottoms (Bonell, 1993; Bruijnzeel, 2004). Thus, the value of $F_{p,o}$ can be substantially above zero if the rainfall has a significant temporal autocorrelation, with heavy rainfall on subsequent days being more likely than would be expected from general rainfall frequencies. If rainfall following a wet day is more likely to occur than following a dry day, as is commonly observed in Markov chain analysis of rainfall patterns (Jones and Thornton, 1997; Bardossy and Plate, 1991), the overland flow component of total flow will also have a partial temporal autocorrelation, adding to the overall predictability of river flow. In a hypothetical climate with evenly distributed rainfall, we can expect F_p to be 1.0 even if there is no infiltration and the only pathway available is overland flow. Even with rainfall that is variable at any point of observation but has low spatial correlation it is possible to obtain F_p values of (close to) 1.0 in a situation with (mostly) overland flow (Ranieri et al., 2004).

2.5 Relationship between flow persistence and flashiness index

The Richards-Baker 'R-B Flashiness index' (Baker et al. 2004) is defined as

$$FI = \sum_t |\Delta Q_t| / \sum_t Q_t = \sum_{ti} (Q_t - Q_{t-1}) + \sum_{td} (Q_{t-1} - Q_t) \qquad [10]$$

with *ti* indicating all times t that $Q_t > Q_{t-1}$ and *td* indicating all times t that $Q_t =< Q_{t-1}$. Over a timeframe that flow has no net trend, the sum of increments ($\sum_{ti} (Q_t - Q_{t-1})$) is equal to the sum of declines ($\sum_{td} (Q_{t-1} - Q_t)$).

Substituting equation [5] in [10] we obtain:

$$FI = 2(1-F_p)(0.5\ \Delta S + \sum_{ti} (P_t - E_{tx} - Q_t)) / \sum_t Q_t = 2(1-F_p)(-0.5\ \Delta S + \sum_{td} (-P_t + E_{tx} + Q_t)) / \sum_t Q_t \qquad [11]$$

With ΔS representing change in catchment storage; $\Delta S = (1-F_p)(-\sum_{ti} (P_t - E_{tx} - Q_t) + \sum_{td} (-P_t + E_{tx} + Q_t))$.

This suggests that $FI = 2(1-F_p)$ is a first approximation and becomes zero for $F_p = 1$. These approximations require that changes in the catchment have no influence on P_t or E_{tx} values. If E_{tx} is negatively affected (either by a change in vegetation or by insufficient buffering, reducing water availability on non-rainfall days) flashiness will increase, beyond the main effects on F_p.

The rainfall term, counted positive for all days with flow increase and negatively for days with declining flow, hints at one of the major reasons why the flashiness index tends to get smaller when larger catchment areas are involved: rainfall will tend to get more evenly distributed over time, unless the spatial correlation of rainfall is (close to) 1 and all rainfall derives from fronts passing over the area uniformly. Where (part of) precipitation occurs as snow, the timing of snow melt defines P_t as used here. Where vegetation influences timing and synchrony of snowmelt, this will be reflected in the flashiness index. It may not directly influence flow persistence, but will be accounted for in the flow description that uses flow persistence as key parameter.

3. Methods

3.1 River flow data for four tropical watersheds

To test the applicability of the F_p metric and explore its properties, data from four Southeast Asian watersheds were used, that will be described and further analysed in part II. The first watershed data set is the Way Besai (414.4 km^2) in Lampung province, Sumatra, Indonesia (Verbist et al., 2010). With an elevation between 720-1831 m a.s.l., the Way Besai is dominated by various coffee production systems (64%), with remaining forest (18%), horticulture and crops (12%) and other land uses (6%). Daily rainfall data from 1976 – 2007, was generated by interpolation of eight rainfall stations using Thiessen polygons; data were obtained from BMKG (*Agency on Meteorology, Climatology and Geophysics*), PU (Public Work Agency) and PLN (*National Electricity Company*). The average of annual rainfall was 2474 mm, with observed values in the range 1216 – 3277 mm. River flow data at the outflow of the Way Besai was also obtained from PU and PUSAIR (*Centre for Research and Development on Water Resources),* with an average of river flow of 16.7 m^3/s.

Data from three other watersheds were used to explore the variation of F_p across multiple years and its relationship with the Flashiness Index: Bialo (111.7 km^2) in South Sulawesi, Indonesia with Agroforestry as the dominant land cover type, Cidanau (241.6 km^2) in West Java, Indonesia, dominated by mixed Agroforestry land uses but with a peat swamp before the final outlet and Mae Chaem (3892 km^2) in Northern Thailand, part of the upper Ping Basin, and dominated by evergreen, deciduous and pine forest. Detailed information on these watersheds and the data sources is provided in Paper II.

3.2 Numerical examples

For visualizing the effects of stochastic rainfall on river flow according to equation [1] a spreadsheet model that is available from the authors on request was used in 'Monte Carlo' simulations. Fixed values for F_p were used in combination with a stochastic $Q_{a,t}$ value. The latter was obtained from a random generator (rand) with two settings for a (truncated) sinus-based daily rainfall probability: A) one for situations that have approximately 120 rainy days, and an annual Q of around 1600 mm, and B) one that leads to around 45 rainy days and an annual total around 600 mm. Maximum daily $Q_{a,t}$ was chosen as 60 mm in both cases. For the figures, realizations for various F_p values were retained that were within 10% of this number of rainy days and annual flow total, to focus on the effects of F_p as such.

3.3 Flow persistence as a simple flood risk indicator

For numerical examples (implemented in a spreadsheet model) flow on each day can be derived as:

$$Q_t = \Sigma_j^t F_p^{t-j} (1-F_p)\, p_j\, P_j \qquad [12].$$

Where p_j reflects the occurrence of rain on day j (reflecting a truncated sine distribution for seasonal trends) and P_j is the rain depth (drawn from a uniform distribution). From this model the effects of F_p (and hence of changes in F_p) on maximum daily flow rates, plus maximum flow totals assessed over a 2-5 days period, was obtained in a Monte Carlo process (without Markov autocorrelation of rainfall in the default case – see below). Relative flood protection was calculated as the difference between peak flows (assessed for 1-5 days duration after a 1 year 'warm-up' period) for a given F_p versus those for $F_p = 0$, relative to those at $F_p = 0$.

3.4 An algorithm for deriving F_p from a time series of stream flow data

Equation (3) provides a first method to derive F_p from empirical data if these cover a full hydrologic year. In situations where there is no complete hydrograph and/or in situations where we want to quantify F_p for shorter time periods (e.g. to characterise intraseasonal flow patterns) and the change in the storage term of the water budget equation cannot be ignored, we need an algorithm for estimating F_p from a series of daily Q_t observations.

Where rainfall has clear seasonality, it is attractive and indeed common practice to derive a groundwater recession rate from a semi-logarithmic plot of Q against time (Tallaksen, 1995). As we can assume for such periods that $Q_{a,t} = 0$, we obtain $F_p = Q_t / Q_{t-1}$, under these circumstances. We cannot be sure, however, that this $F_{p,g}$ estimate also applies in the rainy season, because overall wet-season F_p will include contributions by $F_{p,o}$ and $F_{p,i}$ as well (compare Eq. 9). In locations without a distinct dry season, we need an alternative method.

A biplot of Q_t against Q_{t-1} will lead to a scatter of points above a line with slope F_p, with points above the line reflecting the contributions of $Q_{a,t} > 0$, while the points that plot on the F_p line itself represent $Q_{a,t} = 0$ mm d^{-1}. There is no independent source of information on the frequency at which $Q_{a,t} = 0$, nor what the statistical distribution of $Q_{a,t}$ values is if it is non-zero. Calculating back from the Q_t series we can obtain an estimate ($Q_{a,Fptry}$) of $Q_{a,t}$ for any given estimate ($F_{p,try}$) of F_p, and select the most plausible F_p value. For high $F_{p,try}$ estimates there will be many negative $Q_{a,t,Fptry}$ values, for low $F_{p,try}$ estimates all $Q_{a,t,Fptry}$ values will be larger. An algorithm to derive a plausible F_p estimate can thus make use of the corresponding distribution of 'apparent Q_a' values as estimates of $F_{p,try}$, calculated as $Q_{a,t,Fptry} = Q_t - F_{p,try}\, Q_{t-1}$. While $Q_{a,t}$ cannot be negative in theory, small negative Q_a estimates are likely when using real-world data with their inherent errors. The FlowPer F_p algorithm (van Noordwijk et al., 2011) derives the distribution of $Q_{a,t,Fptry}$ estimates for a range of $F_{p,try}$ values (Figure 3B) and selects the value $F_{p,try}$ that minimizes the variance $Var(Q_{a,t,Fptry})$ (or its standard deviation) (Figure 3C). It is implemented in a spreadsheet workbook that can be downloaded from the ICRAF website (http://www.worldAgroforestry.org/output/flowper-flow-persistence-model)

➔Figure 3

A consistency test is needed that the high-end Q_t values relate to Q_{t+1} in the same was as do low or medium Q_t values. Visual inspection of Q_{t+1} versus Q_t, with the derived F_p value, provides a qualitative view of the validity of this assumption. The F_p algorithm can be applied to any population of (Q_{t-1}, Q_t) pairs, e.g. selected from a multiyear data set on the basis of 3-month periods within the hydrological year.

3.5 Flashiness and flow separation

Hydrographs analysed for F_p were also used for calculating the Richards-Baker or R-B Flashiness index (Baker et al. 2004) by summing the absolute values of all daily changes in flow. Two common flow separation algorithms (fixed and sliding interval methods, Furey and Gupta, 2001) were used to estimate the base flow fraction at an annual basis. The average of the two was compared to F_p.

4 Results

4.1 Numerical examples

Figure 4 provides two examples, for annual river flows of around 1600 and 600 mm y^{-1}, of the way a change in F_p values (based on Eq. 1) influences the pattern of river flow for a unimodal rainfall regime with a well-developed dry season. The increasing 'spikiness' of the graph as F_p is lowered, regardless of annual flow, indicates reduced predictability of flow on any given day during the wet season on the basis of the flow on the preceding day.

⇨ Figure 4

A bi-plot of river flow on subsequent days for the same simulations (Figure 5) shows two main effects of reducing the F_p value: the scatter increases, and the slope of the lower envelope containing the swarm of points is lowered (as it equals F_p). Both of these changes can provide entry points for an algorithm to estimate F_p from empirical time series, provided the basic assumptions of the simple model apply and the data are of acceptable quality.

⇨ Figure 5

For the numerical examples shown in Figure 4, the relative increase of the maximum daily flow when the F_p value decreased from a value close to 1 (0.98) to nearly 0 depended on the rainfall regime; with lower annual rainfall but the same maximum daily rainfall, the response of peak flows to decrease in F_p became stronger.

4.2 Flood intensity and duration

Figure 6 shows the effect of F_p values in the range 0 to 1 on the maximum flows obtained with a random time series of 'effective rainfall', compared to results for $F_p = 0$. Maximum flows were considered at time scales of 1 to 5 days, in a moving average routine. This way a relative flood protection, expressed as reduction of peak flow, could be related to F_p (Figure 6A).

⇨ Figure 6

Relative flood protection rapidly decreased from its theoretical value of 100% at $F_p = 1$ (when there was no variation in river flow), to less than 10% at F_p values of around 0.5. Relative flood protection was slightly lower when the assessment period was increased from 1 to 5 days (between 1 and 3 days it decreased by 6.2%, from 3 to 5 days by a further 1.3%). Two counteracting effects are at play here: a lower F_p means that a larger fraction ($1-F_p$) of the effective rainfall contributes to river flow, but the increased flow is less persistent. In the example the flood protection in situations where the rainfall during 1 or 2 days causes the peak is slightly stronger than where the cumulative rainfall over 3-5 days causes floods, as typically occurs downstream.

As we expect from equation 5 that peak flow is to ($1-F_p$) times peak rainfall amounts, the effect of a change in F_p not only depends on the change in F_p that we are considering, but also on its initial value. Higher initial F_p values will lead to more rapid increases in high flows for the same reduction in F_p (Figure 6B). However, flood duration rather responds to changes in F_p in a curvilinear manner, as flow persistence implies flood persistence (once flooding occurs), but the greater the flow persistence the less likely such a flooding threshold is passed (Figure 6C). The combined effect may be restricted to about 3 days of increase in flood duration for the parameter values used in the default example, but for different parametrization of the stochastic ε other results might be obtained.

4.3 Algorithm for F_p estimates from river flow time series

The algorithm has so far returned non-ambiguous F_p estimates on any modelled time series data of river flow, as well as for all empirical data set we tested (including all examples tested in part II), although there probably are data sets on which it can breakdown. Visual inspection of Q_{t-1}/Q_t biplots (as in Figure 4) can provide clues to non-homogenous data sets, to potential situations where effective F_p depends on flow level Q_t and where data are not consistent with a straight-line lower envelope. Where river flow estimates were derived from a model with random elements, however, variation in F_p estimates was observed, that suggests that specific aspects of actual rainfall, beyond the basic characteristics of a watershed and its vegetation, do have at least some effect. Such effects deserve to be further explored for a set of case studies, as their strength probably depends on context.

4.4 Flow persistence compared to base flow and flashiness index

Figure 7 compares results for a hydrograph of a single year for the Way Besai catchment, described in more detail in paper II. While there is agreement on most of what is indicated as baseflow, the short term response to peaks in the flow differ, with baseflow in the F_p method more rapidly increasing after peak events.

⇨ Figure 7

When compared across multiple years for four Southeast Asian catchments (figure 8A), there is partial agreement in the way interannual variation is described in each catchment, while numerical values are similar. However, the ratio of what is indicated as baseflow according to the F_p method and according to standard hydrograph separation varies from 1.05 to 0.86.

⇨ Figure 8

Figure 8 compares numerical results for the R-B Flashiness Index with F_p for the four test catchments and for a number of hydrographs constructed as in Fig. 3A. The two concepts are inversely related, as expected from equation [11], but where F_p is constrained to the 0-1 interval, the R-B Flashiness Index can attain values up to 2.0, with the value for $F_p = 0$ depending on properties of the local rainfall regime. Where hydrographs were generated with a simple flow model with F_p parameter as key variable, the flashiness index is more tightly related to, especially for higher F_p values, than where both flashiness index and F_p were derived from existing flow data (Figure 8C versus 8B). The difference in slope between the four watersheds in Fig. 8B appears to be primarily related to aspects of the local rainfall pattern that deserve further analysis in larger data sets of this nature.

5 Discussion

We will discuss the flow persistence metric based on the seven questions raised from the perspectives of salience, credibility and legitimacy and refer back to figure 2 that clarified how ecosystem structure, ecosystem function and human land use interact in causal loops that can lead to flood damage, its control and/or prevention.

5.1 Salience

Key *salience* aspects are “Does flow persistence relate to important aspects of watershed behaviour?” and “Does it help to select management actions?”. A major finding in the derivation of F_p was that the flow persistence measured at daily time scale can be logically linked to the long-term water balance under the assumption that the watershed is defined on the basis of actual groundwater flows, and that the proportion of peak rainfall that translates to peak river flow equals the complement of flow persistence. This feature links effects on floods of changes in watershed quality, as commonly expressed in curve numbers and flashiness indices, to effects on low flows, as commonly expressed in base flow metrics. The F_p parameter as such does not predict when and where flooding will occur, but it does help to assess to what extent another condition of the watershed, with either higher or lower F_p would translate the same rainfall into larger or small peak water flows. This is salient, especially if the relative contributions of (anthropogenic) land cover and the (exogenous, probabilistic) specifics of the rainfall pattern can be further teased apart (see part II). Where F_p may describe the descending branch of hydrographs at a relevant time scale, details of the ascending branch beyond the maximum daily flow reached may be relevant for reducing flood damage, and may require more detailed study at higher temporal resolution.

Figures 3 and 6 show that most of the effects of a decreasing F_p value on peak discharge (which is the basis for downstream flooding) occur between F_p values of 1 and 0.7, with the relative flood protection value reduced to 10% when F_p reaches 0.5. As indicated in Figure 2, peak discharge is only one of the factors contributing to flood risk in terms of human casualties and physical damage. Flood risks are themselves nonlinearly and in strongly topography-specific ways related to the volume of river flow after extreme rainfall events. While the expected fraction of rainfall that contributes to direct flow is linearly related to rainfall via (1-Fp), flooding risk as such will have a non-linear relationship with rainfall, that depends on topography and antecedent rainfall. Catchment changes, such as increases or decreases in percentage tree cover, will generally have a non-linear relationship with F_p as well as with flooding risks. The F_p value has an inverse effect on the fraction of recent rainfall that becomes river flow, but the effect on peak flows is less, as higher F_p values imply higher base flow. The way these counteracting effects balance out depends on details of the local rainfall pattern (including its Markov chain temporal autocorrelation), as well as the downstream topography and risk of people being at the wrong time at a given place, but the F_p value is an efficient way of summarizing complex land use mosaics and upstream topography in its effect on river flow. The difference between wet-season and dry-season F_p deserves further analysis. In climates with a real rainless dry-season, dry season F_p is dominated by the groundwater release fraction of the watershed, regardless of land cover, while in wet season it depends on the mix (weighted average) of flow pathways. The degree to which F_p can be influenced by land cover needs to be assessed for each landscape and land cover combination, including the locally relevant forest and forest derived land classes, with their effects on interception, soil infiltration and time pattern of transpiration. The F_p value can summarize results of models that explore land use change scenarios in local context. To select the specific management actions that will maintain or increase F_p a locally calibrated land use/hydrology model is needed, such as GenRiver (part II), DHV (Bergström, 1995) or SWAT (Yen et al., 2015).

The ‘health’ wording has been used as a comprehensive concept of the way a) climate forcing, b) watershed vegetation and soil conditions and c) engineering interventions interact on functional aspects of river flow. Ma et al (2014) described a method to separate these three influences on river flow. In the four catchments we used as example there have been no major dams or reservoirs installed upstream of the points of measurement. Where these do exist the specific operating rules of reservoirs need to be included in any model and these can have a major influence on downstream flow, depending on the primary use for power generation, dry season irrigation or stabilizing river flow for riverine transport. Although a higher F_p value will in most cases be desirable (and a decrease in F_p undesirable), we may expect that In an ecological perspective on watershed health, the change in low flows that can occur in the flow regime of degrading and intensively managed watersheds alike, depending on the management rules for reservoirs, is at least as relevant as changes in flood risks, as many aquatic organisms thrive during floods (Pahl-Wostl et al., 2013; Poff et al., 2010). Downstream biota can be expected to have adapted to the pre-human flow conditions, inherent F_p and variability. Decreased variability of flow achieved by engineering interventions (e.g. a reservoir with constant release of water to generate hydropower) may have negative consequences for fish and other biota (Richter et al., 2003; McCluney et al., 2014). In an extensive literature review Poff and Zimmerman (2010) found no general, transferable quantitative relationships between flow alteration and ecological response, but the risk of ecological change increases with increasing magnitude of flow alteration.

Various geographically defined watershed health concepts are in use (see for example https://www.epa.gov/hwp/healthy-watersheds-projects-region-5; City of Fort Collins, 2015, employing a range of specific indicators, including the ‘R-B flashiness index’ (Baker et al. 2004). The definition of watershed health, like that of human health has evolved over time. Human health was seen as a state of normal function that could be disrupted from time to time by disease. In 1948 the World Health Organization (1958) proposed a definition that aimed higher, linking health to well-being, in terms of physical, mental, and social aspects, and not merely the absence of disease and infirmity. Health became seen as the ability to maintain homeostasis and recover from injury, but remained embedded in the environment in which humans function.

5.2 Credibility

Key *credibility* questions are “Consistency of numerical results?” and “How sensitive are results to bias and random error in data sources?”. A key strength of our flow persistence parameter, that it can be derived from a limited number of observations of river flow at a single point along the river, without knowledge of rainfall events and catchment conditions, is also its major weakness. If rainfall data exist, and especially rainfall data that apply to each subcatchment, the Q_a term doesn’t have to be treated as a random variable and event-specific information on the flow pathways may be inferred for a more precise account of the hydrograph. But for the vast majority of rivers in the tropics, advances in remotely sensed rainfall data are needed to achieve that situation and F_p may be all that is available to inform public debates on the location-specific relation between forests and floods.

The main conclusions from the numerical examples analysed so far are that intra-annual variability of F_p values between wet and dry seasons was around 0.2, interannual variability in either annual or seasonal F_p was generally in the 0.1 range, while the difference between observed and simulated flow data as basis for F_p calculations was mostly less than 0.1. With current methods, it seems that effects of land cover change on flow persistence that shift the F_p value by about 0.1 are the limit of what can be asserted from empirical data (with shifts of that order in a single year a warning sign rather than a firmly established change). When derived from observed river flow data F_p is suitable for monitoring change (degradation, restoration) and can be a serious candidate for monitoring performance in outcome-based ecosystem service management contracts. In interpreting changes in F_p as caused by changes in the condition in the watershed, however, changes in specific properties of the rainfall regime must be excluded. At the scale of paired catchment studies this assumption may be reasonable, but in temporal change (or using specific events as starting point for analysis), it is not easy to disentangle interacting effects (Ma et al., 2014). Recent evidence that vegetation not only responds to, but also influences rainfall (arrow 10 in Figure 2; van Noordwijk et al., 2015b) further complicates the analysis across scales.

As indicated, the F_p method is related to earlier methods used in streamflow hydrograph separation of base flow and quick flow. While textbooks (Ward and Robinson, 2000; Hornberger et al 2014) tend to be critical of the lack of objectivity of graphical methods, algorithms are used for deriving the minimum flow in a fixed or sliding period of reference as base flow (Sloto and Crouse, 1996; Furey and Gupta, 2001). The time interval used for deriving the minimum flow depends on catchment size.

Recursive models that describe flow in a next time interval on the basis of a fraction of that in the preceding time interval with a term for additional flow due to additional rainfall have been used in analysis of peak flow event before, with time intervals as short as 1 minute rather than the 1 day we use here (Rose, 2004). Through reference to an overall mass balance a relationship similar to what we found here (F_p times preceding flow plus 1 – F_p times recent inputs) was also used in such models. To our knowledge, the method we describe here at daily timescales has not been used before.

The idea that the form of the storage-discharge function can be estimated from analysis of streamflow fluctuations has been explored before for a class of catchments in which discharge is determined by the volume of water in storage (Kirchner, 2009). Such catchments behave as simple first-order nonlinear dynamical systems and can be characterized in a single-equation rainfall-runoff model that predicted streamflow, in a test catchment in Wales, as accurately as other models that are much more highly parameterized. This model of the dQ/dt versus Q relationship can also be analytically inverted; thus, it can, according to Kirchner (2009), be used to "do hydrology backward," that is, to infer time series of whole-catchment precipitation directly from fluctuations in streamflow. The slope of the log-log relationship between flow recession (dQ/dt) and Q that Kirchner (2009) used is conceptually similar to the F_p metric we derived here, but the specific algorithm to derive the parameter from empirical data differs. Further exploration of the underlying assumptions is needed. Estimates of dQ/dt are sensitive to noise in the measurement of Q and the possibly frequent and small increases in Q can be separated from the expected flow recession in the algorithm we presented here.

Table 1 compares a number of properties (Salience and Legitimacy in properties 1-4, Credibility dimensions in 5-10) for the R-B Flashiness Index (Baker et al. 2004) and flow persistence. The main advantage of continuing with the flashiness index is that there is an empirical basis for comparisons and the index has been included in existing 'watershed health' monitoring programs, especially in the USA. The main advantage of including F_p is that it can be estimated from incomplete flow records, has a clear link to peak flow events and has a more direct relationship with underlying flow pathways, changes in rainfall (or snowmelt) and evapotranspiration, reflecting land cover change.

➔ Table 1

Seibert and Beven (2009) discussed the increase in predictive skill of models depending on the amount of location-specific data that can be used to constrain them. They found that the ensemble prediction of multiple models for a single location clearly outperformed the predictions using single parameter sets and that surprisingly little runoff data was necessary to identify model parameterizations that provided good results for 'ungauged' test periods in cases where actual measurements were available. Their results indicated that a few runoff measurements can contain much of the information content of continuous runoff time series. The way these conclusions might be modified if continuous measurements for limited time periods, rather than separated single data points on river flow could be used, remains to be explored. Their study indicated that results may differ significantly between catchments and critical tests of F_p across multiple situations are obviously needed, as paper II will provide.

In discussions and models of temperate zone hydrology (Bergström, 1995; Seibert, 1999) snowmelt is a major component of river flow and effects of forest cover on spring temperatures are important to the buffering of the annual peaks in flow that tend to occur in this season. Application of the F_p method to data describing such events has yet to be done.

5.3 Legitimacy

Legitimacy aspects are "Does it match local knowledge?" and "Can it be used to empower local stakeholders of watershed management?" and "Can it inform risk management?". As the F_p parameter captures the predictability of river flow that is a key aspect of degradation according to local knowledge systems, its results are much easier to convey than full hydrographs or exceedance probabilities of flood levels. By focusing on observable effects at river level, rather than prescriptive recipes for land cover ("Reforestation"), the F_p parameter can be used to more effectively compare the combined effects of land cover change, changes in the riparian wetlands and engineered water storage reservoirs, in their effect on flow buffering. It is a candidate for shifting environmental service reward contracts from input to outcome based monitoring (van Noordwijk et al., 2012). As such it can be used as part of a negotiation support approach to natural resources management in which levelling off on knowledge and joint fact finding in blame attribution are key steps to negotiated solutions that are legitimate and seen to be so (van Noordwijk et al., 2013; Leimona et al., 2015). Quantification of F_p can help assess tactical management options (Burt et al., 2014) as in a recent suggestion to minimize negative downstream impacts of forestry operations on stream flow by avoiding land clearing and planting operations in locally wet La Niña years. But the most challenging aspect of the management of flood, as any other environmental risk, is that the frequency of disasters is too low to intuitively influence human behaviour where short-term risk taking benefits are attractive. Wider social pressure is needed for investment in watershed health (as a type of insurance premium) to be mainstreamed, as individuals waiting to see evidence of necessity are too late to respond. In terms of flooding risk, actions to restore or retain watershed health can be similarly justified as insurance premium. It remains to be seen whether or not the transparency of the F_p metric and its intuitive appeal are sufficient to make the case in public debate when opportunity costs of foregoing reductions in flow buffering by profitable land use are to be compensated and shared (Burt et al., 2014).

6 Conclusions

In conclusion, the F_p metric appears to allow an efficient way of summarizing complex landscape processes into a single parameter that reflects the effects of landscape management within the context of the local climate. If rainfall patterns change but the landscape does not, the resultant flow patterns may reflect a change in watershed health (van Noordwijk et al., 2016). Flow persistence is the result of rainfall persistence and the temporal delay provided by the pathway water takes through the soil and the river system. High flow persistence indicates a reliable water supply, while minimizing peak flow events. Wider tests of the F_p metric as boundary object in science-practice-policy boundary chains (Kirchhoff et al., 2015; Leimona et al., 2015) are needed. Further tests for specific case studies can clarify how changes in tree cover (deforestation, reforestation and agroforestation) in different contexts influence river flow dynamics and F_p values. Sensitivity to specific realizations of underlying time-space rainfall patterns needs to be quantified, before changes in F_p can be attributed to changed 'watershed health', rather than chance events.

Author contributions

Meine van Noordwijk designed method and paper, Lisa Tanika refined the empirical algorithm and handled the case study data and modelling for part II, and Betha Lusiana contributed statistical analysis; all contributed and approved the final manuscript

Acknowledgements

This research is part of the Forests, Trees and Agroforestry research program of the CGIAR. Several colleagues contributed to the development and early tests of the F_p method. Thanks are due to Eike Luedeling, Sonya Dewi, Sampurno Bruijnzeel and three anonymous reviewers for comments on an earlier version of the manuscript.

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Figures:

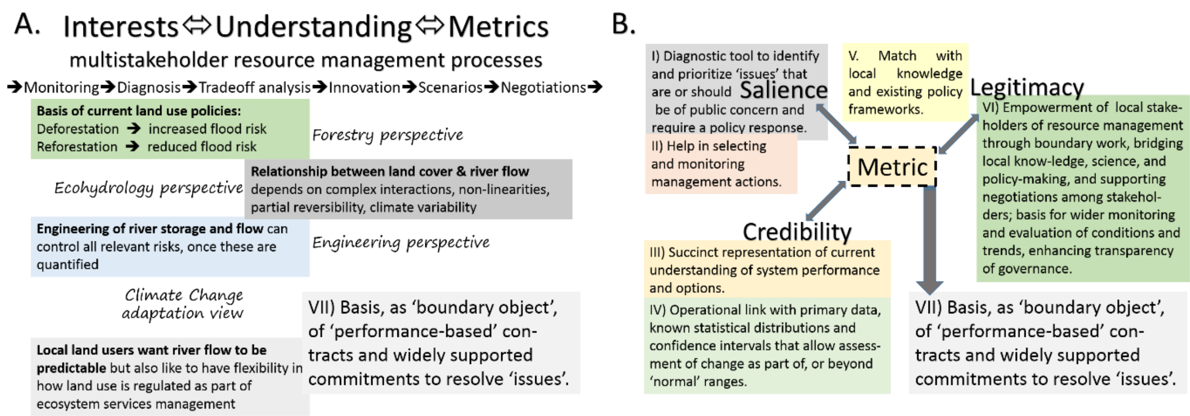

Figure 1. A. Multiple perspectives on the way flood risk is to be understood, monitored and handled according to different knowledge systems; B. Basic requirements for a 'metric' to be used in public discussions of natural resource management issues that deserve to be resolved and acted upon (modified from van Noordwijk et al., 2016)

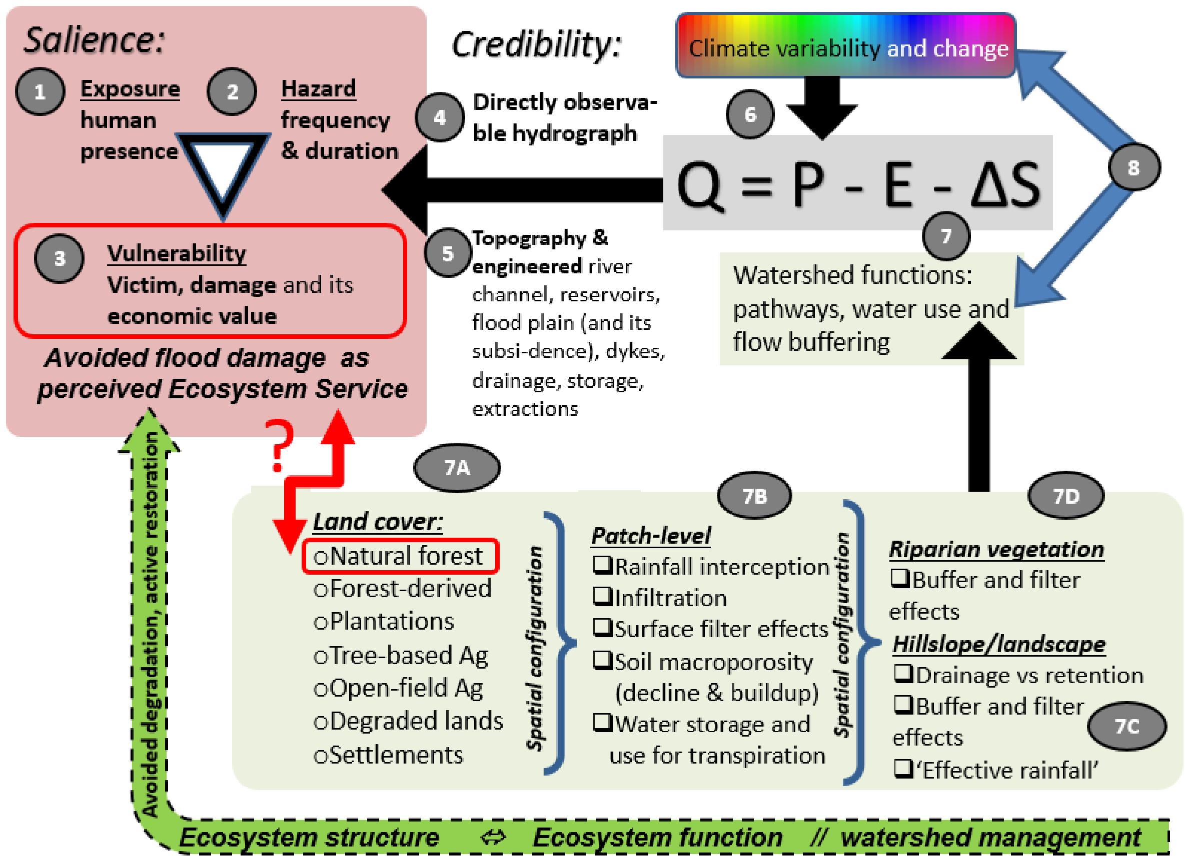

Figure 2. Steps in a causal pathway that relates the salience of 'avoided flood damage as ecosystem service' to the interaction of exposure (1; being in the wrong place at critical times), hazard (2; spatially explicit flood frequency and duration) and human determinants of vulnerability (3); the hazard component depends, in common scientific analysis, on the pattern of river flow described in a hydrograph (4), which in turn is understood to be influenced by conditions along the river channel (5), precipitation and potential evapotranspiration (E_{pot} as climatic factors (6) and the condition in the watershed (7) determining evapotranspiration (E_{act}), temporary water storage (ΔS) and water partitioning over overland flow and infiltration; these watershed functions in turn depend on the interaction of terrain (topography, soils, geology), vegetation and human land use; current understanding of a two-way interaction between vegetation and rainfall adds further complexity (8)

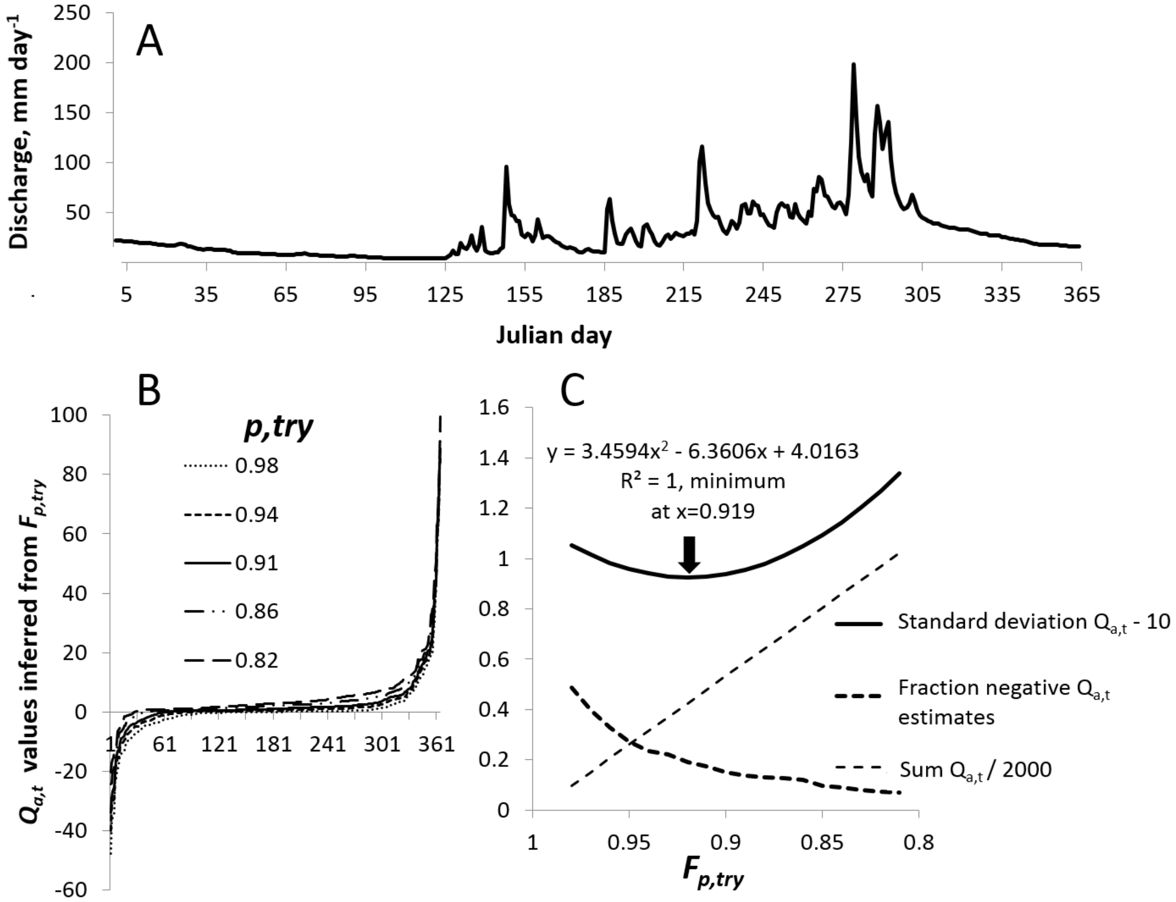

Figure 3. Example of the derivation of best fitting $F_{p,try}$ value for an example hydrograph (A) on the basis of the inferred Q_a distribution (cumulative frequency in B), and three properties of this distribution (C): its sum, frequency of negative values and standard deviation; the $F_{p,try}$ minimum of the latter is derived from the parameters of a fitted quadratic equation

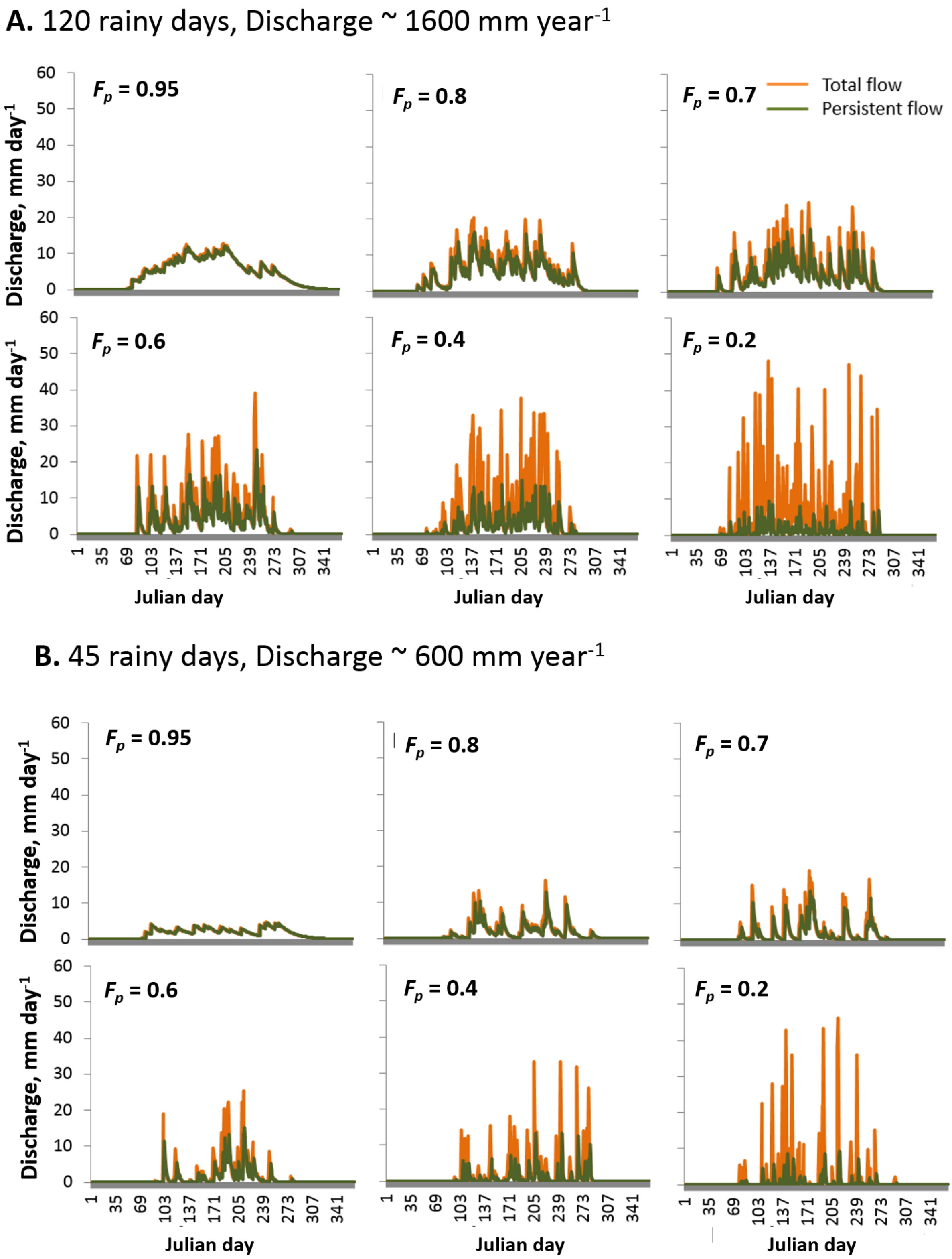

Figure 4. Effects of the F_p parameter on hydrographs of daily river flow generated by a random rainfall generator, with persistent and additional flow components indicated, for two settings with total rainfall of approximately 1600 and 600 mm/yr (NB river flow is here expressed as mm d^{-1} rather than as m^3 s^{-1} as in figure 3)

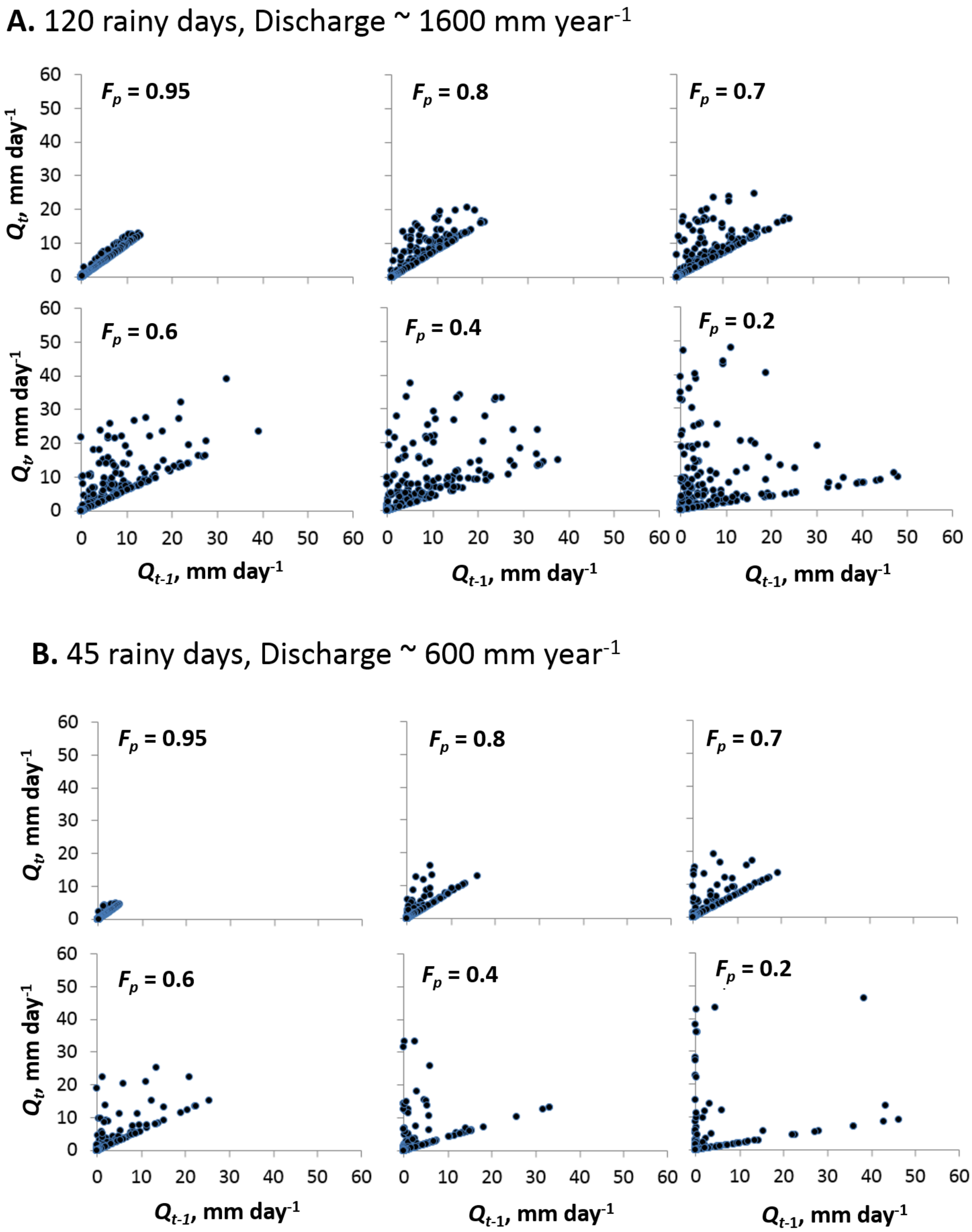

Figure 5 A and B Temporal autocorrelation of river flow for the same simulations as Figure 4; the lower envelope of the points indicated slope F_p, the points above this line the effect of fresh additions to river flow

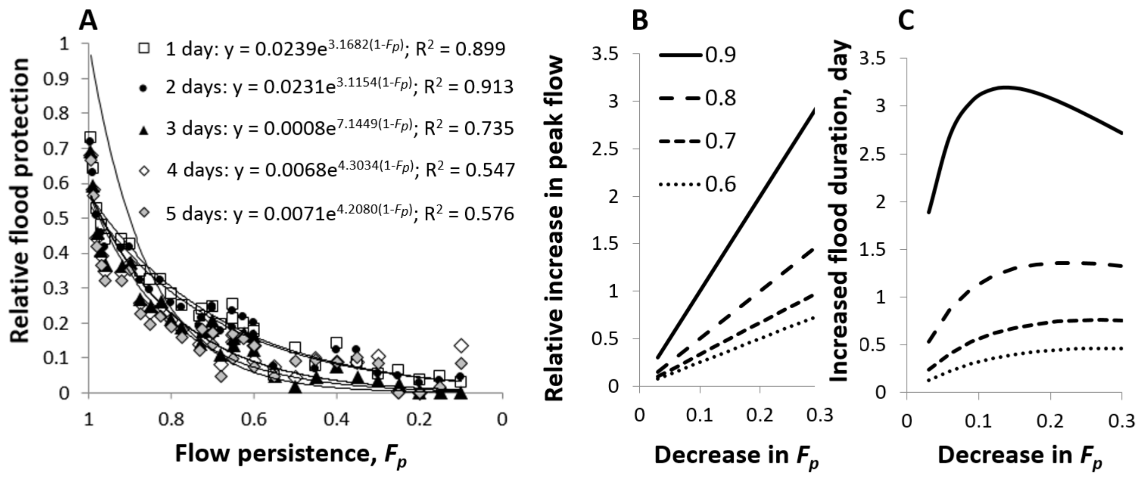

Figure 6. A. Effects of flow persistence on the relative flood protection (decrease in maximum flow measured over a 1 – 5 d period relative to a case with $F_p = 0$ (a few small negative points were replaced by small positive values to allow the exponential fit); B and C. effects of a decrease in flow persistence on the volume of water involved in peak flows (B; relative to the volume at F_p is 0.6 – 0.9) and in the duration (in d) of floods (C)

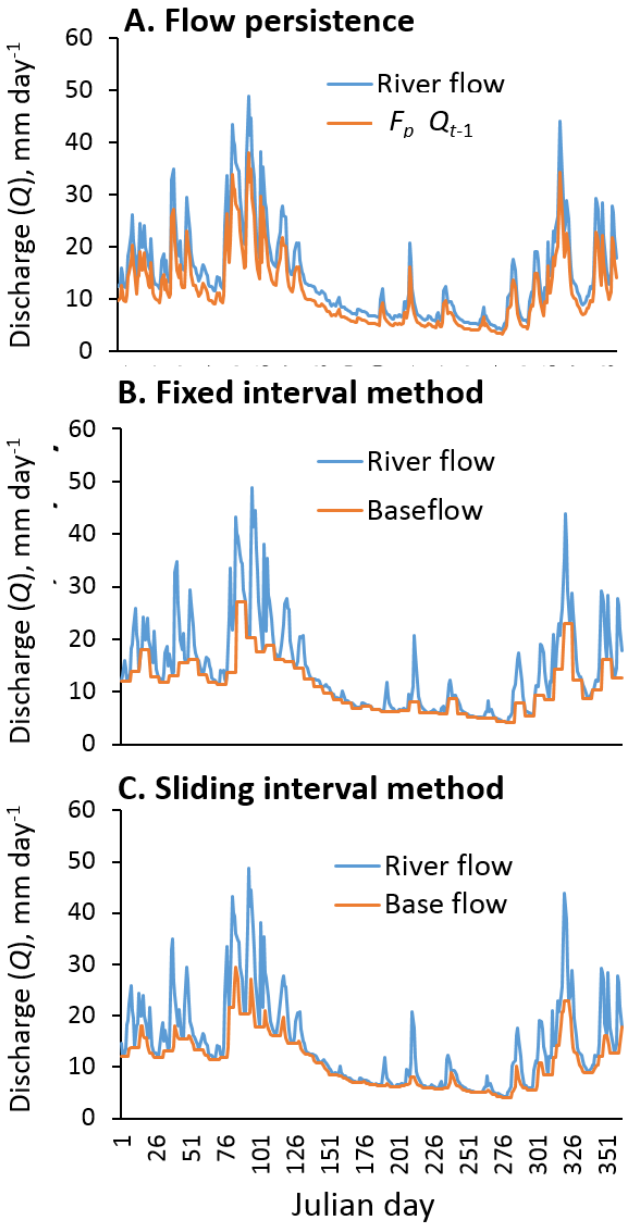

Figure 7. Comparison of base flow separation of a hydrograph according to the flow persistence method (A) and two common flow separation methods, respectively with fixed (B) and sliding intervals (C)

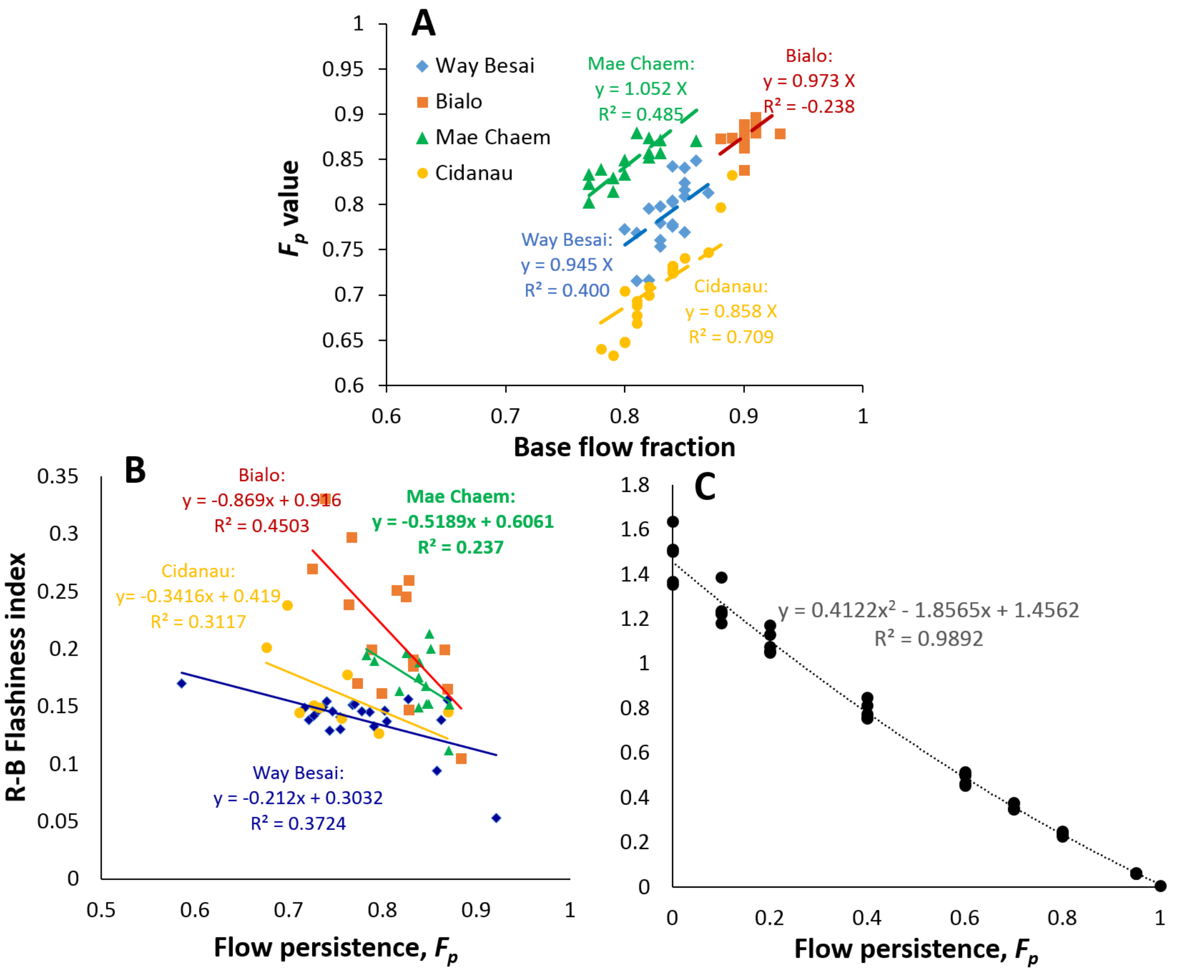

Figure 8. A) Comparison of yearly data for four Southeast Asian watersheds analysed with common flow separation methods (average of results in Fig. 7) and the flow persistence method and comparison of the Richards-Baker Flashiness Index (Baker et al., 2004) and the flow persistence metric F_p for B) four Southeast Asian watersheds, C) a series of hydrographs as in Fig. 4A, with 5 replicates per F_p value

Table 1. Comparison of properties of the Flashiness Index and Flow persistence F_p

	Flashiness Index (Baker et al. 2004)	Flow persistence (as defined here)
1.	Has direct appeal to non-technical audiences	Potentially similar
2.	Where reservoir management rules imply major changes in ΔS, flashiness still describes implications for flow regimes	Is focused on the effects of changes in (upper) catchment land cover, not where reservoir management determines flow
3.	Values depend on the scale of evaluating river flow; no absolute criteria for what is 'healthy'	Similar
4.	Increase generally not desirable	Decrease generally not desirable
5.	Varies in range [0-2], may need normalizing by division by 2	Varies in range [0-1]

6. Requires full year flow record to be calculated	Can be estimated from any set of sequential flow observations
7. Empirical metric, no direct link to underlying process understanding	Overall F_p can be understood as weighted average of the F_p's of contributing flow pathways (overland, subsurface and groundwater-based)
8. No directly visible relationship between peak and low flow characteristics	The F_p term low flows and the (1 - F_p) term for peak flows show the water balance logic of a link between peak and low flows
9. Aggregates changes in flow regime; no directly visible link between the performance metric, rainfall (or snow melt) and (vegetation dependent) evapotranspiration	The main water balance terms are directly reflected in the flow descriptions based on F_p
10. Substantial empirical data bases available for comparison and meta studies	Not yet

Flood risk reduction and flow buffering as ecosystem services: II. Land use and rainfall intensity effects in Southeast Asia

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Abstract

Watersheds buffer the temporal pattern of river flow relative to the temporal pattern of rainfall. This ‘ecosystem service’ is inherent to geology and climate, but buffering also responds to human use and misuse of the landscape. Buffering can be part of management feedback loops if salient, credible and legitimate indicators are used. The flow persistence parameter F_p in a parsimonious recursive model of river flow (Part I) couples the transmission of extreme rainfall events (1- F_p), to the annual base flow fraction of a watershed (F_p). Here we compare F_p estimates from four meso-scale watersheds in Indonesia (Cidanau, Way Besai, and Bialo) and Thailand (Mae Chaem), with varying climate, geology and land cover history, at a decadal time scale. The likely response in each of these four to variation in rainfall properties (incl. the maximum hourly rainfall intensity) and land cover (comparing scenarios with either more or less forest and tree cover than the current situation) was explored through a basic daily water balance model, GenRiver. This model was calibrated for each site on existing data, before being used for alternative land cover and rainfall parameter settings. In both data and model runs, the wet-season (3-monthly) F_p values were consistently lower than dry-season values for all four sites. Across the four catchments F_p values decreased with increasing annual rainfall, but specific aspects of watersheds, such as the riparian swamp (peat soils) in Cidanau reduced effects of land use change in the upper watershed. Increasing the mean rainfall intensity (at constant monthly totals for rainfall) around the values considered typical for each landscape was predicted to cause a decrease in F_p values by between 0.047 (Bialo) and 0.261 (Mae Chaem). Sensitivity of F_p to changes in land use change plus changes in rainfall intensity depends on other characteristics of the watersheds, and generalizations made on the basis of one or two case studies may not hold, even within the same climatic zone. A wet-season F_p value above 0.7 was achievable in forest-Agroforestry mosaic case studies. Interannual variability in F_p is large relative to effects of land cover change. Multiple (5-10) years of paired-plot data would generally be needed to reject no-change null-hypotheses on the effects of land use change (degradation and restoration). F_p trends over time serve as a holistic scale-dependent performance indicator of degrading/recovering watershed health and can be tested for acceptability and acceptance in a wider social-ecological context.

Introduction

Inherent properties (geology, geomorphology) interact with climate and human modification of vegetation, soils, drainage and riparian wetlands in effectuating the degree of buffering that watersheds provide (Andréassian 2004; Bruijnzeel, 2004). Buffering of river flow relative to the space-time dynamics of rainfall is an ecosystem service, reducing the exposure of people living on geomorphological floodplains to high-flow events, and increasing predictability and river flow in dry periods (Joshi et al., 2004; Leimona et al., 2015; Part I). In the absence of any vegetation and with a sealed surface, river flow will directly respond to the spatial distribution of rainfall, with only the travel time to any point of specific interest influencing the temporal pattern of river flow. Any persistence or predictability of river flow in such a situation will reflect temporal autocorrelation of rainfall, beyond statistical predictability in seasonal rainfall patterns. On the other side of the spectrum, river flow can be constant every day, beyond the theoretical condition of constant rainfall, in a watershed that provides perfect buffering, by passing all water through groundwater pools that have sufficient storage capacity at any time during the year. Both infiltration-limited (Hortonian) and saturation-induced use of more rapid flow pathways (inter and overland flows) will reduce the flow persistence and make it, at least in part, dependent on rainfall events. Separating the effects of land cover (land use), engineering and rainfall on the actual flow patterns of rivers remains a considerable challenge (Ma et al., 2014; Verbist et al., 2019). It requires data, models and concepts that can serve as effective boundary object in communication with stakeholders (Leimona et al. 2015; van Noordwijk et al. 2012, 2016). There is a long tradition in using forest cover as such a boundary object, but there is only a small amount of evidence supporting this (Tan-Soo et al., 2014; van Dijk et al., 2009; van Noordwijk et al. 2015a; part I).

In part I, we introduced a flow persistence parameter (F_p) that links the two, asymmetrical aspects of flow dynamics: translating rainfall excess into river flow, and gradually releasing water stored in the landscape. The direct link between these two aspects can be seen from equation [4] in part I:

$$Q_t = F_p\, Q_{t-1} + (1-F_p)(P_t - E_{tx})$$

Where Q_t and Q_{t-1} represent river flow on subsequent days, P_{tx} the precipitation on day t (or preceding precipitation released as snowmelt on day t) and E_{tx} the preceding evapotranspiration since the previous precipitation event, creating storage space in the soils of the watershed. The first term on the right-hand side of the equation represents the gradual release of stored water, causing a slow decline of flow as the pools feeding this flow are gradually depleted. The second term reflects the part of fresh additions of water are partitioned over immediate river flow and the increase of stocks from which water can be gradually released. The derivation of the link depended on the long term water balance, and thus assumed that all out- and inflows are accounted for in the watershed.

Commonly used rainfall-runoff models (including the curve number approach and SWAT models) only focus on the second term of the above equation (Ponce et al., 1996; Gassman et al., 2007), without link to the first. Various empirical methods for deriving ‘base flow’ are in use, but details of the calculation procedure matter. Results in part I for a number of contrasting meso-scale watersheds in Southeast Asia suggested that interannual variation in F_p within a given watershed correlates with both the R-B Flashiness Index (Baker et al., 2004) and the base-flow fraction of annual river flow. However, the slope of these relationships varied between watersheds. Here, in part II we will further analyse the F_p results for these watersheds that were selected to represent variation in rainfall and land cover, and test the internal consistency of results based on historical data: two located in the humid and one in the subhumid tropics of Indonesia, and one in the unimodal subhumid tropics of northern Thailand.

After exploring the patterns of variation in F_p estimates derived from actual river flow records, we will quantify the sensitivity of the F_p metric to variations in rainfall intensity and its response, on a longer timescale to land cover change. To do so, we will use a model that uses basic water balance concepts: rainfall interception, infiltration, water use by vegetation, overland flow, interflow and groundwater release, to a spatially structured watershed where travel time from sub watersheds to any point of interest modifies the predicted river flow. In the specific model used land cover effects on soil conditions, interception and seasonal water use have been included. After testing whether F_p values derived from model outputs match those based on empirical data where these exist, we rely on the basic logic of the model to make inference on the relative importance of modifying rainfall and land cover inputs. With the resulting temporal variation in calculated F_p values, we consider the time frame at which observed shifts in F_p can be attributed to factors other than chance (that means: null-hypotheses of random effects can be rejected with accepted chance of Type I errors).

2. Methods

2.1 GenRiver model for effects of land cover on river flow

The GenRiver model (van Noordwijk et al., 2011) is based on a simple water balance concept with a daily time step and a flexible spatial subdivision of a watershed that influences the routing of water and employs spatially explicit rainfall. At patch level, vegetation influences interception, retention for subsequent evaporation and delayed transfer to the soil surface, as well as the seasonal demand for water. Vegetation (land cover) also influences soil porosity and infiltration, modifying the inherent soil properties. Water in the root zone is modelled separately for each land cover within a subcatchment, the groundwater stock is modelled at subcatchment level. The spatial structure of a watershed and the routing of surface flows influences the time delays to any specified point of interest, which normally includes the outflow of the catchment. Land cover change scenarios are interpolated annually between time-series (measured or modelled) data. The model may use measured rainfall data, or use a rainfall generator that involves Markov chain temporal autocorrelation (rain persistence). As our data sources are mostly restricted to daily rainfall measurements and the infiltration model compares instantaneous rainfall to infiltration capacity, a stochastic rainfall intensity was applied at subcatchment level, driven by the mean as parameter and a standard deviation for a normal distribution (truncated at 3 standard deviations from the mean) proportional to it via a coefficient of variation as parameter. For the Mae Chaem site in N Thailand data by Dairaku et al. (2004) suggested a mean of less than 3 mm/hr. For the three sites in Indonesia we used 30 mm/hr, based on Kusumastuti et al. (2016). Appendix 1 provides further detail on the GenRiver model. The model itself, a manual and application case studies are freely available (http://www.worldAgroforestry.org/output/genriver-genetic-river-model-river-flow;van Noordwijk et al., 2011).

2.2 Empirical data-sets, model calibration

Table 1 and Figure 1 provide summary characteristics and the location of river flow data used in four meso-scale watersheds for testing the F_p algorithm and application of the GenRiver model. Figure 1 includes a water tower category in the agro-ecological zones; this is defined on the basis of a ratio of precipitation and potential evapotranspiration of more than 0.65, and a product of that ratio and relative elevation exceeding 0.277.

⇨ Table 1
⇨ Figure 1

As major parameters for the GenRiver model were not independently measured for the respective watersheds, we tuned (calibrated) the model by modifying parameters within a predetermined plausible range, and used correspondence with measured hydrograph as test criterion (Kobolt et al. 2008). We used the Nash-Sutcliff Efficiency (NSE) parameter (target above 0.5) and bias (less than 25%) as test criteria and targets. Meeting these performance targets (Moriasi et al., 2007), we accepted the adjusted models as basis for describing current conditions and exploring model sensitivity. The main site-specific parameter values are listed in Table 2 and (generic) land cover specific default parameters in Table 3.

⇨ Table 2
⇨ Table 3

Table 4 describes the six scenarios of land use change that were evaluated in terms of their hydrological impacts. Further description on the associated land cover distribution for each scenario in the four different watersheds is depicted in Appendix 2.

⇨ Table 4

2.3 Bootstrapping to estimate the minimum observation

The bootstrap methods (Efron and Tibshirani, 1986) is a resampling methods that is commonly used to generate 'surrogate population' for the purpose of approximating the sampling distribution of a statistic. In this study, the bootstrap approach was used to estimate the minimum number of observation (or yearly data) required for a pair-wise comparison test between two time-series of stream flow or discharge data (representing two scenarios of land use distributions) to be distinguishable from a null-hypothesis of no effect. The pair-wise comparison test used was Kolmogorov-Smirnov test that is commonly used to test the distribution of discharge data (Zhang eta al, 2006). We built a simple macro in R (R Core Team, 2015) that entails the following steps:

(i) Bootstrap or resample with replacement 1000 times from both time-series discharge data with sample size *n*;

(ii) Apply the Kolmogorov-Smirnov test to each of the 1000 generated pair-wise discharge data, and record the P-value;

(iii) Perform (i) and (ii) for different size of *n*, ranging from 5 to 50.

(iv) Tabulate the p-value from the different sample size *n*, and determine the value of *n* when the p-value reached equal to or less than 0.025 (or equal to the significance level of 5%). The associated *n* represents the minimum number of observations required.

Appendix 3 provides an example of the macro in R used for this analysis.

3. Results

3.1 Empirical data of flow persistence as basis for model parameterization

Inter-annual variability of F_p estimates derived for the four catchments (Figure 2) was of the order of 0.1 units, while the intra-annual variability between dry and rainy seasons was 0.1-0.2. For all years and locations, rainy season F_p values, with mixed flow pathways, were consistently below dry-season values, dominated by groundwater flows. If we can expect $F_{p,i}$ and $F_{p,o}$ (see equation 8 in part I) to be approximately 0.5 and 0, this difference between wet and dry periods implies a 40% contribution of interflow in the wet season, a 20% contribution of overland flow or any combination of the two effects.

Overall the estimates from modelled and observed data are related with 16% deviating more than 0.1 and 3% more than 0.15 (Figure 3). As the Moriasi et al. (2007) performance criteria for the hydrographs were met by the calibrated models for each site, we tentatively accept the model to be a basis for sensitivity study of Fp to modifications to land cover and/or rainfall

- ⇨ Figure 2
- ⇨ Figure 3

3.2 Comparing F_p effects of rainfall intensity and land cover change

A direct comparison of model sensitivity to changes in mean rainfall intensity and land use change scenarios is provided in Figure 4. Varying the mean rainfall intensity over a factor 7 shifted the F_p value by only 0.047 and 0.059 in the case of Bialo and Cidanau, respectively, but by 0.128 in Way Besai and 0.261 in Mae Chaem (Figure 4A). The impact of the land use change scenarios on F_p was smallest in Cidanau (0.026), intermediate in Way Besai (0.048) and relatively large in Bialo and Mae Chaem, at 0.080 and 0.084, respectively (Figure 4B). The order of F_p across the land use change scenarios was mostly consistent between the watersheds, but the contrast between the Reforestation and Natural Forest scenario was largest in Mae Chaem and smallest in Way Besai. In Cidanau, Way Besai and Mae Chaem, variations in rainfall were 2.2 to 3.1 times more effective than land use change in shifting F_p, in Bialo its relative effect was only 58%. Apparently, the sensitivity to changes in land use change plus changes in rainfall intensity depends on other characteristics of the watersheds, and generalizations made on the basis of one or two case studies may not hold, even within the same climatic zone.

- ⇨ Figure 4

3.3 Further analysis of F_p effects for scenarios of land cover change

Among the four watersheds there is consistency in that the 'forest' scenario has the highest, and the 'degraded lands' the lowest F_p value (Figure 5), but there are remarkable differences as well: in Cidanau the interannual variation in F_p is clearly larger than land cover effects, while in the Way Besai the spread in land use scenarios is larger than interannual variability. In Cidanau a peat swamp between most of the catchment and the measuring point buffers most of land cover related variation in flow, but not the interannual variability. Considering the frequency distributions of F_p values over a 20 year period, we see one watershed (Way Besai) where the forest stands out from all others, and one (Bialo) where the degraded lands are separate from the others. Given the degree of overlap of the frequency distributions, it is clear that multiple years of empirical observations will be needed before a change can be affirmed.

Figure 5 shows the frequency distributions of expected effect sizes on F_p of a comparison of any land cover with either forest or degraded lands. Table 5 translates this information to the number of years that a paired plot (in the absence of measurement error) would have to be maintained to reject a null-hypothesis of no effect, at p=0.05. As the frequency distributions of F_p differences of paired catchments do not match a normal distribution, a Kolmorov-Smirnov test can be used to assess the probability that a no-difference null hypothesis can yield the difference found. By bootstrapping within the years where simulations supported by observed rainfall data exist, we found for the Way Besai catchment, for example, that 20 years of data would be needed to assert (at P = 0.05) that the Reforestation scenario differs from Agroforestation, and 16 years that it differs from Actual and 11 years that it differs from Degrade. In practice, that means that empirical evidence that survives statistical tests will not emerge, even though effects on watershed health are real.

⇨ Figure 5

⇨ Table 5

At process-level the increase in 'overland flow' in response to soil compaction due to land cover change has a clear and statistically significant relationship with decreasing F_p values in all catchments (Figure 6), but both year-to-year variation within a catchment and differences between catchments influence the results as well, leading to considerable spread in the biplot. Contrary to expectations, the disappearance of 'interflow' by soil compaction is not reflected in measurable change in F_p value. The temporal difference between overland and interflow (one or a few days) gets easily blurred in the river response that integrates over multiple streams with variation in delivery times; the difference between overland- or interflow and baseflow is much more pronounced. Apparently, according to our model, the high macroporosity of forest soils that allows interflow and may be the 'sponge' effect attributed to forest, delays delivery to rivers by one or a few days, with little effect on the flow volumes at locations downstream where flow of multiple days accumulates. The difference between overland- or interflow and baseflow in time-to-river of rainfall peaks is much more pronounced.

⇨ Figure 6

Tree cover has two contradicting effects on baseflow: it reduces the surplus of rainfall over evapotranspiration (annual water yield) by increased evapotranspiration (especially where evergreen trees or trees with a large canopy interception are involved), but it potentially increases soil macroporosity that supports infiltration and interflow, with relatively little effect on water holding capacity measured as 'field capacity' (after runoff and interflow have removed excess water). Figure 7 shows that the total volume of baseflow differs more between sites and their rainfall pattern than it varies with tree cover. Between years total evapotranspiration and baseflow totals are positively correlated, but for a given rainfall there is a trade-off. Overall these results support the conclusion that generic effects of deforestation on decreased flow persistence, and of (agro)/(re)-forestation on increased flow persistence are small relative to interannual variability due to specific rainfall patterns, and that it will be hard for any empirical data process to pick-up such effects, even if they are qualitatively aligned with valid process-based models.

⇨ Figure 7

4. Discussion

In the discussion of Part I the credibility questions on replicability of the F_p metric and its sensitivity to details of rainfall pattern versus land cover as potential causes of variation were seen as requiring case studies in a range of contexts. Although the four case studies in Southeast Asia presented here cannot be claimed to represent the global variation in catchment behaviour (with absence of a snowpack and its dynamics as an obvious element of flow buffering not included), the diversity of responses among these four already point to challenges for any generic interpretation of the degree of flow persistence that can be achieved under natural forest cover, as well as its response to land cover change.

The empirical data summarized here for (sub)humid tropical sites in Indonesia and Thailand show that values of F_p above 0.9 are scarce in the case studies provided, but values above 0.8 were found, or inferred by the model, for forested landscapes. Agroforestry landscapes generally presented F_p values above 0.7, while open-field agriculture or degraded soils led to F_p values of 0.5 or lower. Due to differences in local context, it may not be feasible to relate typical F_p values to the overall condition of a watershed, but temporal change in F_p can indicate degradation or restoration if a location-specific reference can be found. The difference between wet and dry season F_p can be further explored in this context. The dry season F_p value primarily reflects the underlying geology, with potential modification by engineering and operating rules of reservoirs, the wet season F_p is generally lower due to partial shifts to overland and interflow pathways. Where further uncertainty is introduced by the use of modelled rather than measured river flow, the lack of fit of models similar to the ones we used here would mean that scenario results are indicative of directions of change rather than a precision tool for fine-tuning combinations of engineering and land cover change as part of integrated watershed management.

The differences in relative response of the watersheds to changes in mean rainfall intensity and land cover change, suggest that generalizations derived from one or a few case studies are to be interpreted cautiously. If land cover change would influence details of the rainfall generation process (arrow 10 in Figure 1 of part I; e.g. through release of ice-nucleating bacteria Morris et al., 2014; van Noordwijk et al., 2015b) this can easily dominate over effects via interception, transpiration and soil changes.

Our results indicate an intra-annual variability of F_p values between wet and dry seasons of around 0.2 in the case studies, while interannual variability in either annual or seasonal F_p was generally in the 0.1 range. The difference between observed and simulated flow data as basis for F_p calculations was mostly less than 0.1. With current methods, it seems that effects of land cover change on flow persistence that shift the F_p value by about 0.1 are the limit of what can be asserted from empirical data (with shifts of that order in a single year a warning sign rather than a firmly established change). When derived from observed river flow data F_p is suitable for monitoring change (degradation, restoration) and can be a serious candidate for monitoring performance in outcome-based ecosystem service management contracts. Choice of the part of the year for which F_p changes are used as indicator may have to depend on the seasonal patterns of rainfall.

In view of our results the lack of robust evidence in the literature of effects of change in forest and tree cover on flood occurrence may not be a surprise; effects are subtle and most data sets contain considerable variability. Yet, such effects are consistent with current process and scaling knowledge of watersheds.

In summarizing findings on the F_p metric, we can compare it with existing ones across the seven questions raised in Fig. 1 of part I. Comparator metrics can derive from various data sources, including the amount (and/or quality) of forest cover upstream, the fraction of flows that is technically controlled, direct records of river flow (over a short or longer time period), records of rainfall and/or models that combine landscape properties, climate and land cover. Tentative scoring for these metrics (Table 6) suggest that the F_p metric is an efficient tool for data-scarce environments, as it indicates aspects of hydrographs that so far required multi-annual records of river flow.

➔Table 6

Conclusion

Overall, our analysis suggests that the level of flow buffering achieved depends on both land cover (including its spatial configuration and effects on soil properties) and space-time patterns of rainfall (including maximum rainfall intensity as determinant of overland flow). Generalizations on dominant influence of either, derived from one or a few case studies are to be interpreted cautiously. If land cover change would influence details of the rainfall generation process this can easily dominate over effects via interception, transpiration and soil changes. Multi-year data will generally be needed to attribute observed changes in flow buffering to degradation/restoration of watersheds, rather than specific rainfall events. With current methods, it seems that effects of land cover change on flow persistence that shift the F_p value by about 0.1 are the limit of what can be asserted from empirical data, with shifts of that order in a single year a warning sign rather than a firmly established change. When derived from observed river flow data F_p is suitable for monitoring change (degradation, restoration) and can be a serious candidate for monitoring performance in outcome-based ecosystem service management contracts. Watershed health is here characterized through the flow pattern it generates, leaving the attribution to land cover, rainfall pattern and engineering of that pattern and of changes in pattern to further location-specific analysis, just as a symptom of a high body temperature can indicate health, but not diagnose the specific illness causing it.

The data sets analysed so far did not indicate that the flow persistence at high flows differed from that at lower flows within the same season, but in other circumstances this may not be the case and further care may be needed to use F_p values beyond the measurement period in which they were derived. While a major strength of the F_p method over existing procedures for parameterizing curve number estimates, for example, is that the latter depend on scarce observations during extreme events and F_p can be estimated for any part of the flow record, the reliability of F_p estimates will still increase with the length of the observation period.

Further tests on the performance of the F_p metric and its standard incorporation into the output modules of river flow and watershed management models will broaden the basis for interpreting the value ranges that can be expected for well-functioning watersheds in various conditions of climate, topography, soils, vegetation and engineering interventions. Such a broader empirical base could test the possible use of F_p as performance metric for watershed rehabilitation efforts.

Data availability

Table 7 specifies the rainfall and river flow data we used for the four basins and specifies the links to detailed descriptions.

⇨ Table 7

Acknowledgements

This research is part of the Forests, Trees and Agroforestry research program of the CGIAR. Several colleagues contributed to the development and early tests of the F_p method. Thanks are due to Thoha Zulkarnain for assistance with Figure 1 and to Eike Luedeling, Sonya Dewi, Sampurno Bruijnzeel and two anonymous reviewers for comments on an earlier version of the manuscript.

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Table 1. Basic physiographic characteristics of the four study watersheds

Parameter	Bialo	Cidanau	Mae Chaem	Way Besai
Location	South Sulawesi, Indonesia	West Java, Indonesia	Northern Thailand	Lampung, Sumatera, Indonesia
Coordinates	5.43 S, 120.01 E	6.21 S, 105.97 E	18.57 N, 98.35 E	5.01 S, 104.43 E
Area (km^2)	111.7	241.6	3892	414.4
Elevation (m a.s.l.)	0 – 2874	30 – 1778	475-2560	720-1831
Flow pattern	Parallel	Parallel (with two main river flow that meet in the downstream area)	Parallel	Radial
Land cover type	Forest (13%) Agroforest (59%) Crops (22%) Others (6%)	Forest (20%) Agroforest (32%) Crops (33%) Others (11%) Swamp(4%)	Forest (evergreen, deciduous and pine) (84%) Crops (15%) Others (1%)	Forest (18%) Coffee (monoculture and multistrata) (64%) Crop and Horticulture (12%) Others (6%)
Mean annual rainfall, mm	1695	2573	1027	2474
Wet season	April – June	January - March	July - September	January - March
Dry season	July - September	July - September	January - March	July - September
Mean annual runoff, mm	947	917	259	1673
Major soils	Inceptisols	Inceptisols	Ultisols, Entisols	Andisols

Table 2. Parameters of the GenRiver model used for the four site specific simulations (van Noordwijk et al., 2011 for definitions of terms; sequence of parameters follows the pathway of water)

Parameter	**Definition**	**Unit**	**Bialo**	**Cidanau**	**Mae Chaem**	**Way Besai**
RainIntensMean	Average rainfall intensity	mm hr^{-1}	30	30	3	30
RainIntensCoefVar	Coefficient of variation of rainfall intensity	mm hr^{-1}	0.8	0.3	0.5	0.3

RainInterceptDripRt	Maximum drip rate of intercepted rain	mm hr^{-1}	80	10	10	10
RainMaxIntDripDur	Maximum dripping duration of intercepted rain	hr	0.8	0.5	0.5	0.5
InterceptEffectontrans	Rain interception effect on transpiration	-	0.35	0.8	0.3	0.8
MaxInfRate	Maximum infiltration capacity	mm d^{-1}	580	800	150	720
MaxInfSubsoil	Maximum infiltration capacity of the sub soil	mm d^{-1}	80	120	150	120
PerFracMultiplier	Daily soil water drainage as fraction of groundwater release fraction	-	0.35	0.13	0.1	0.1
MaxDynGrWatStore	Dynamic groundwater storage capacity	mm	100	100	300	300
GWReleaseFracVar	Groundwater release fraction, applied to all subcatchments	-	0.15	0.03	0.05	0.1
Tortuosity	Stream shape factor	-	0.4	0.4	0.6	0.45
Dispersal Factor	Drainage density	-	0.3	0.4	0.3	0.45
River Velocity	River flow velocity	m s^{-1}	0.4	0.7	0.35	0.5

Table 3. GenRiver defaults for land use specific parameter values, used for all four watersheds (BD/BDref indicates the bulk density relative to that for an agricultural soil pedotransfer function; see van Noordwijk et al., 2011)

Land cover Type	Potential interception (mm/d)	Relative drought threshold	BD/BDref
Forest[1]	3.0 - 4.0	0.4 - 0.5	0.8 - 1.1
Agroforestry[2]	2.0 - 3.0	0.5 - 0.6	0.95 - 1.05
Monoculture tree[3]	1.0	0.55	1.08
Annual crops	1.0 - 3.0	0.6 - 0.7	1.1 - 1.5
Horticulture	1.0	0.7	1.07
Rice field[4]	1.0 - 3.0	0.9	1.1 - 1.2
Settlement	0.05	0.01	1.3
Shrub and grass	2.0 - 3.0	0.6	1.0 - 1.07
Cleared land	1.0 - 1.5	0.3 - 0.4	1.1 - 1.2

Note: 1. Forest: primary forest, secondary forest, swamp forest, evergreen forest, deciduous forest

2. Agroforestry: mixed garden, coffee, cocoa, clove

3. Monoculture : coffee

4. Rice field: irrigation and rainfed

Table 4. Land use scenarios explored for four watersheds

Scenario	Description
Natural Forest	Full natural forest, hypothetical reference scenario
Reforestation	Reforestation, replanting shrub, cleared land, grass land and some agricultural area with forest
Agroforestation	Agroforestry scenario, maintaining Agroforestry areas and converting shrub, cleared land, grass land and some of agricultural area into Agroforestry
Actual	Baseline scenario, based on the actual condition of land cover change during the modelled time period
Agriculture	Agriculture scenario, converting some of tree based plantations, cleared land, shrub and grass land into rice fields or dry land agriculture, while maintain existing forest
Degrading	No change in already degraded areas, while converting most of forest and Agroforestry area into rice fields and dry land agriculture

Table 5. Number of years of observations required to estimate flow persistence to reject the null-hypothesis of 'no land use effect', at p-value = 0.05 using Kolmogorov-Smirnov test. The probability of the test statistic in the first significant number is provided between brackets and where the number of observations exceeds the time series available, results are given in *italics*

A. Natural Forest as reference

Way Besai (N=32)	Refores-tation	Agrofo-restation	Actual	Agricultural
Reforestation		20 (0.035)	16 (0.037)	13 (0.046)
Agroforestation			n.s.	n.s.
Actual				n.s.
Agricultural				
Degrading				

Bialo (N=18)				
Reforestation		n.s.	n.s.	*37 (0.04)*
Agroforestation			n.s.	n.s.
Actual				n.s.
Agricultural				
Degrading				

Cidanau (N=20)				
Reforestation		n.s.	n.s.	*32 (0.037)*
Agroforestation			n.s.	n.s.
Actual				n.s.
Agricultural				
Degrading				

Mae Chaem (N=15)				
Reforestation		n.s.	*23 (0.049)*	*18 (0.050)*
Agroforestation			*45 (0.037)*	*33 (0.041)*

Actual				*33 (0.041)*
Agricultural				

B. **Degrading scenario as reference**

Way Besai (N=32)	Natural forest	Reforestation	Agrofo-restation	Actual	Agriculture
Natural forest		n.s.	17 (0.042)	13 (0.046)	7 (0.023)
Reforestation			21 (0.037)	19 (0.026)	7 (0.023)
Agroforestation				n.s.	28 (0.046)
Actual					30 (0.029)
Agriculture					

Bialo (N=18)					
Natural forest		n.s.	n.s.	*41 (0.047)*	*19 (0.026)*
Reforestation			n.s.	n.s.	*32 (0.037)*
Agroforestation				n.s.	n.s.
Actual					n.s.
Agricultural					

Cidanau (N=20)					
Natural forest		n.s.	n.s.	*33 (0.041)*	8 (0.034)
Reforestation			n.s.	n.s.	15 (0.028)
Agroforestation				n.s.	n.s.
Actual					*25 (0.031)*
Agricultural					

Mae Chaem (N=15)	Natural forest	Reforestation	Actual	Agriculture
Natural forest		n.s.	25 (0.031)	12 (0.037)
Reforestation			n.s.	*18 (0.050)*

Agroforestation		*18 (0.050)*
Actual		

Table 6. Comparison of metrics at various points in the causal network (Fig. 2 of Paper I) that can support watershed management and prevention of flood damage on the list of seven issues (I – VII) introduced in Fig. 1 Paper I*.

	Terrain-based (7A and 5 in Fig. 2 of part I)		Based on river flow characteristics (4 in Fig. 2 of part I)						Integrated (5-7) terrain + climate + land use + river flow models	
Issues*	Forest cover	Fraction of flow technically regulated	Q_{max} / Q_{min}	Flashiness index	Flow frequency analysis	Curve-number (rainfall-runoff)	Base-flow	Flow persistence, F_p	Spatial analysis	Spatial water flow model
Range	0-100%	0–100%	1 - ω	0 - 2		1 - 100	0-100%	0 - 1		
IA	No	Yes	No	Yes	Yes	Yes	No	Yes	Partially	Yes
IB	No	Yes	No	No	Yes	No	Yes	Yes	Partially	Yes
IIA	Not	Partially	Not	Not	Yes	Partially	Partially	Partially	Partially	Partially
IIB	Partially	Yes	Not	Not	Not	Partially	Partially	Partially	Partially	Yes
IIC	Not	Partially	Not	Partially	Partially	Not	Partially	Partially	Partially	Yes
III	Partially	Partially	Not	Partially	Yes	Partially	Partially	Partially	Partially	Yes
IVA	Single	-	Single	Single	Multi	Multi	Single	Single	Single	Single
IVB	Robust	Robust	Sensitive	Sensitive	Sensitive	Sensitive	Robust	Robust	Robust	Robust
V	Partially	Not	Not	Yes	No	No	Partially	Yes	Partially	Partially
VI	Not	Not	Not	Partially	Not	Not	Not	Yes	Partially	Partially
VII	Not	Neutral	Not	Yes	Yes	Neutral	Neutral	Yes	Yes	Yes

I. Does the indicator relate to important aspects of watershed behaviour (A. Flood damage prevention; B. Low flow water availability)?

II. Does its quantification help to select management actions? (A. Risk assessment, insurance design; B. Spatial planning, engineering interventions; C. Fine-tuning land use)

III. Is it consistent with current understanding of key processes

IV. Are data requirements feasible (A. Lowest temporal resolution for estimates (years); B. Consistency of numerical results and sensitivity to bias and random error in data sources?)

V. Does it match local knowledge and concerns?

VI. Can it be used to empower local stakeholders of watershed management through performance (outcome) based contracts?

VII. Can it inform local risk management?

Table 7. Data availability

	Bialo	Cidanau	Mae Chaem	Way Besai
Rainfall data	1989-2009, Source: BWS Sulawesi[a] and PUSAIR[b]; Average rainfall data from the stations Moti, Bulo-bulo, Seka and Onto	1998-2008, source: BMKG[c]	1998-2002, source: WRD55, MTD22, RYP48, GMT13, WRD 52	1976-2007, Source: BMKG, PU[d] and PLN[e] (interpolation of 8 rainfall stations using Thiessen polygon)
River flow data	1993-2010, source; BWS Sulawesi and PUSAIR	2000-2009, source: KTI[f]	1954-2003, source: ICHARM[g]	1976-1998, source: PU and PUSAIR
Reference of detailed report	http://old.icraf.org/regions/southeast_asia/publications?do=view_pub_detail&pub_no=PP0343-14	http://worldAgroforestry.org/regions/southeast_asia/publications?do=view_pub_detail&pub_no=PO0292-13	http://worldAgroforestry.org/regions/southeast_asia/publications?do=view_pub_detail&pub_no=MN0048-11	http://worldAgroforestry.org/regions/southeast_asia/publications?do=view_pub_detail&pub_no=MN0048-11

Note:

[a] BWS: Balai Wilayah Sungai (*Regional River Agency*)

[b]PUSAIR: Pusat Litbang Sumber Daya Air (*Centre for Research and Development on Water Resources)*

[c]BMKG: Badan Meteorologi Klimatologi dan Geofisika (*Agency on Meteorology, Climatology and Geophysics*)

[d]PU: Dinas Pekerjaan Unum *(Public Work Agency)*

[e]PLN: Perusahaan Listrik Negara (*National Electric Company*)

[f]KTI: Krakatau Tirta Industri, a private steel company

[f]ICHARM: The International Centre for Water Hazard and Risk Management

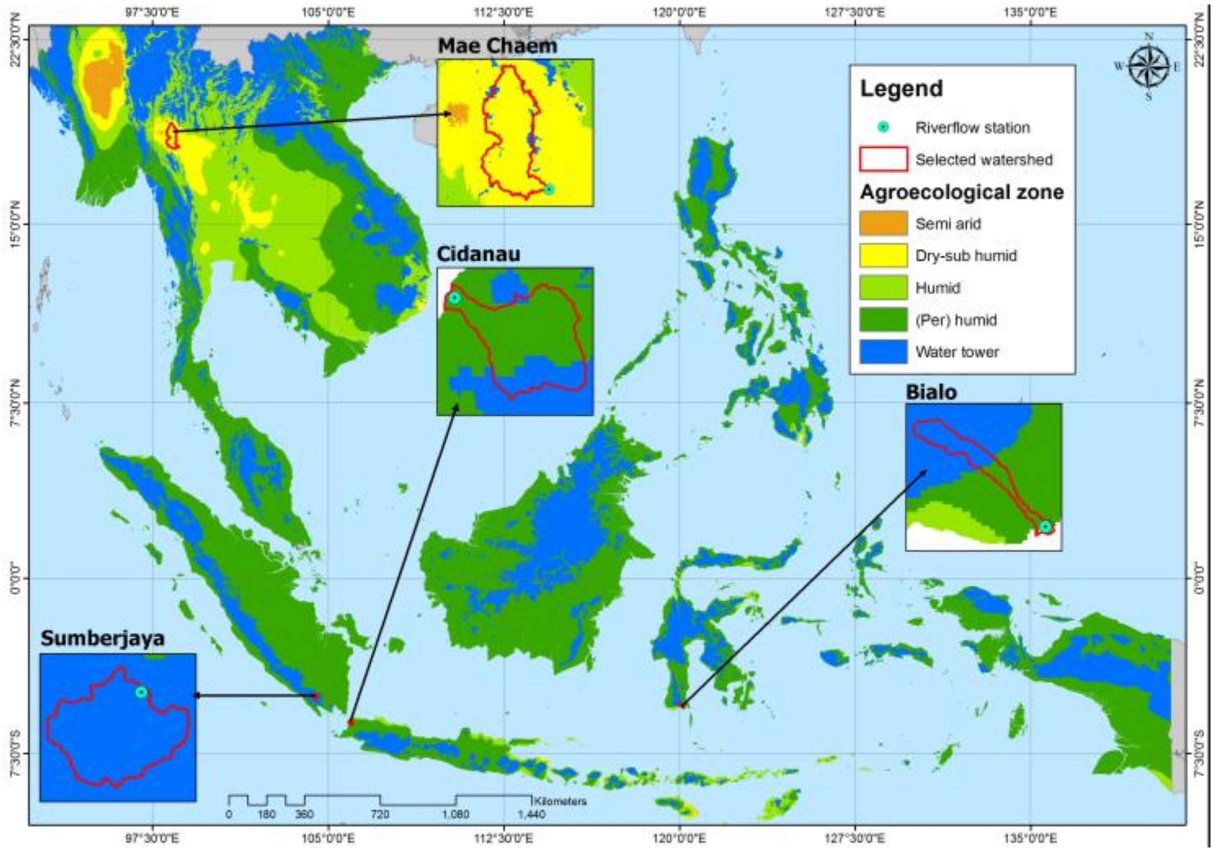

Figure 1. Location of the four watersheds in the agroecological zones of Southeast Asia (water towers are defined on the basis of ability to generate river flow and being in the upper part of a watershed)

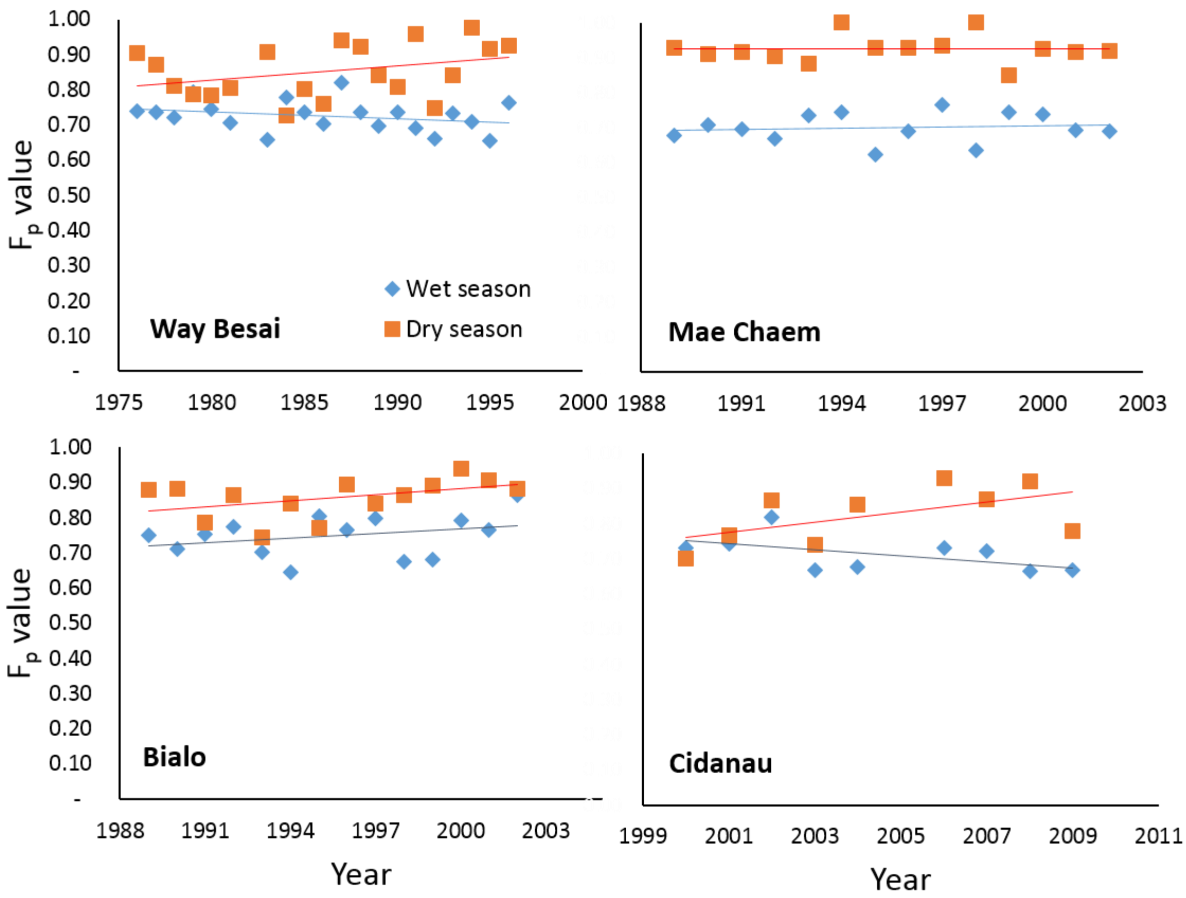

Figure 2. Flow persistence (F_p) estimates derived from measurements in four Southeast Asian watersheds, separately for the wettest and driest 3-month periods of the year

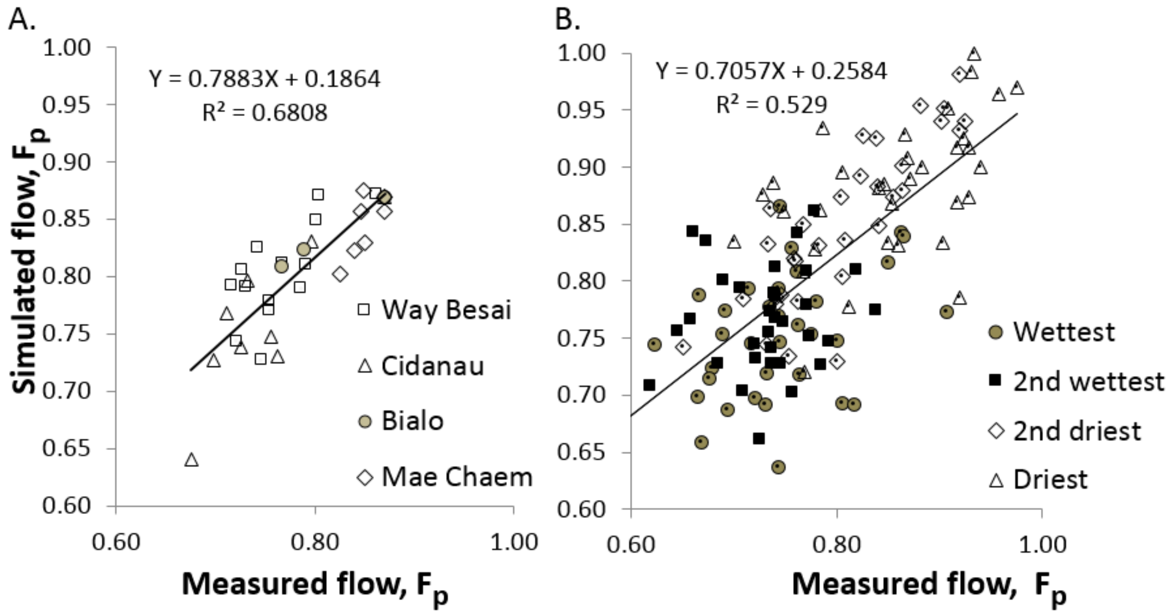

Figure 3. Inter- (A) and intra- (B) annual variation in the F_p parameter derived from empirical versus modelled flow: for the four test sites on annual basis (A) or three-monthly basis (B)

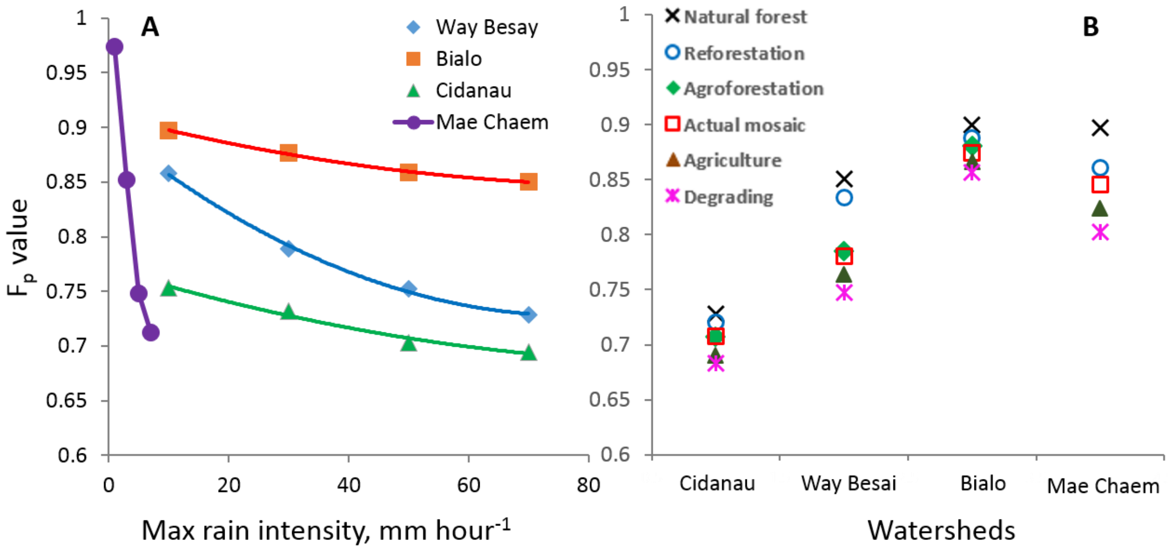

Figure 4 Effects on flow persistence of changes in A) the mean rainfall intensity and B) the land use change scenarios of Table 4 across the four watersheds

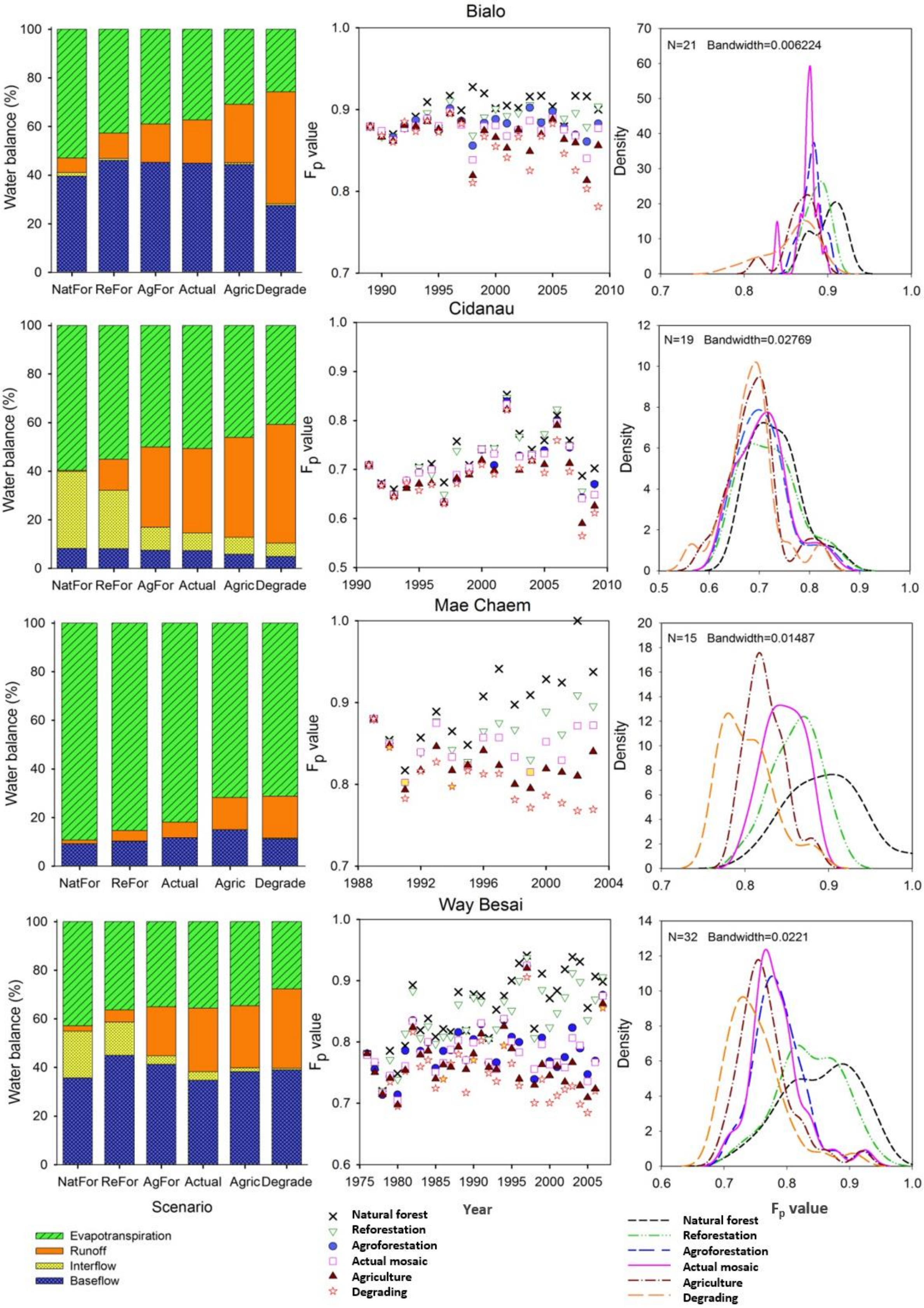

Figure 5. Effects of land cover change scenarios (Table 4) on the flow persistence value in four watersheds, modelled in GenRiver over a 20-year time-period, based on actual rainfall records; the left side panels show average water balance for each land cover scenario, the middle panels

the Fp values per year and land use, the right-side panels the derived frequency distributions (best fitting Weibull distribution)

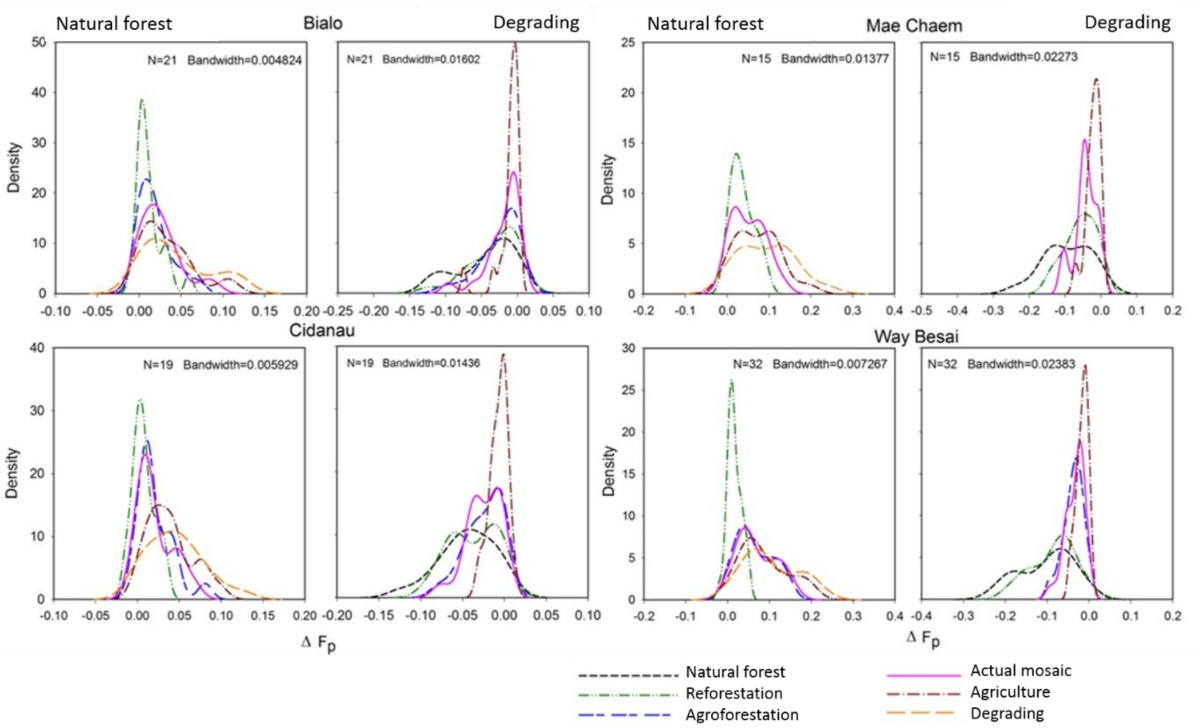

Figure 6. Frequency distribution of expected difference in F_p in ‘paired plot’ comparisons where land cover is the only variable; left panels: all scenarios compared to ‘Reforestation’, right panel: all scenarios compared to degradation; graphs are based on a kernel density estimation (smoothing) approach

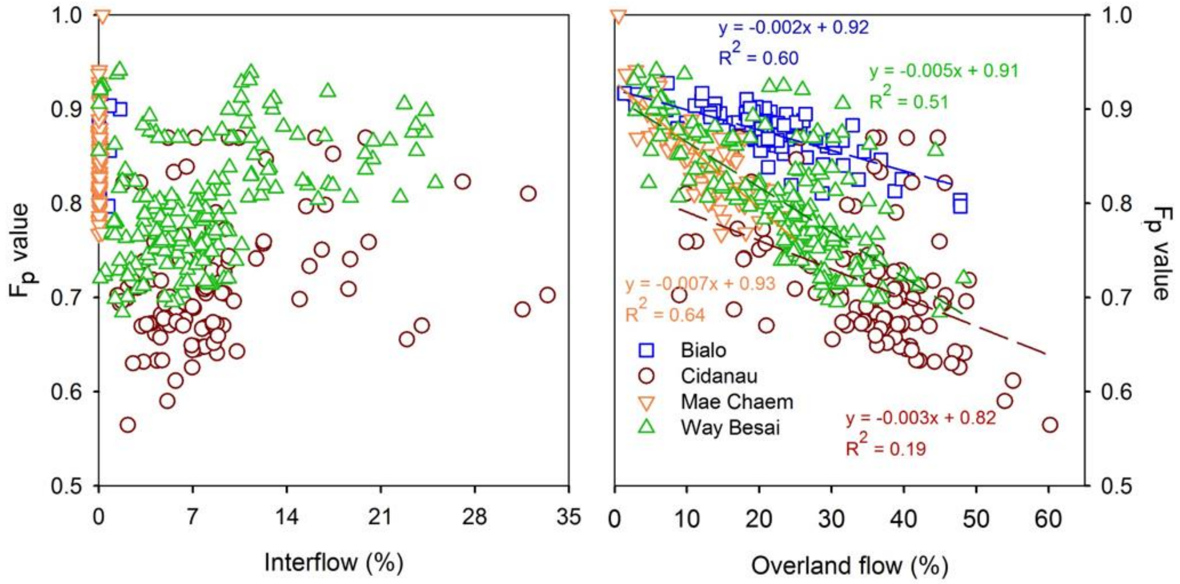

Figure 7. Correlations of F_p with fractions of rainfall that take overland flow and interflow pathways through the watershed, across all years and land use scenarios of Figure App2

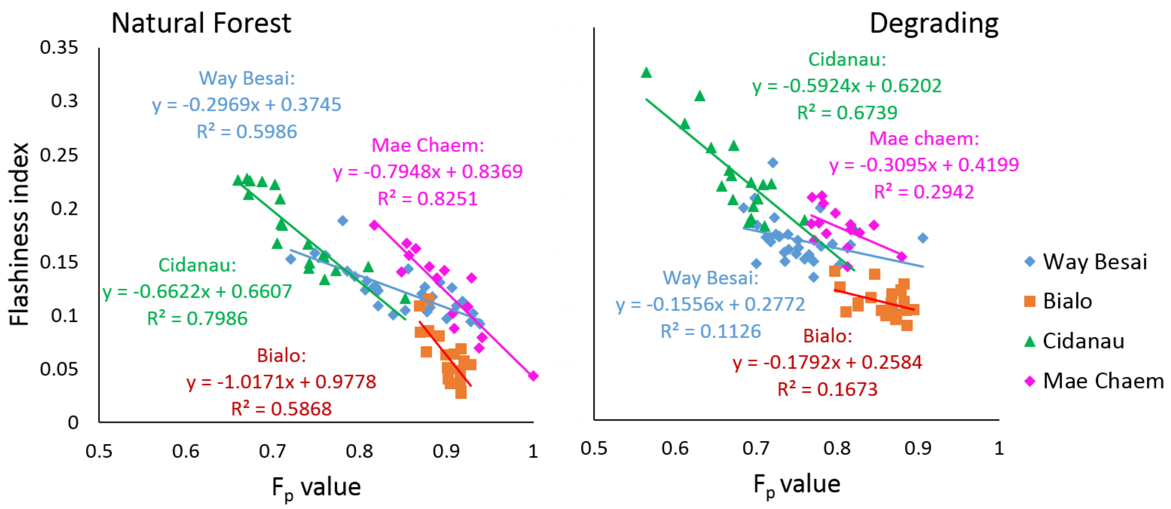

Figure 8. Relationship between F_p value and R-B Flashiness index across years in foru Southeast Asian watersheds under a 'natural forest' and 'degradation' scenario, simulated with the GenRiver model

Appendix 1. GenRiver model for effects of land cover on river flow

The Generic River flow (GenRiver) model (van Noordwijk et al., 2011) is a simple hydrological model that simulates river flow based on water balance concept with a daily time step and a flexible spatial subdivision of a watershed that influences the routing of water. The core of the GenRiver model is a “patch” level representation of a daily water balance, driven by local rainfall and modified by the land cover and land cover change and soil properties. The model starts accounting of rainfall or /precipitation (P) and traces the subsequent flows and storage in the landscape that can lead to either evapotranspiration (E), river flow (Q) or change in storage (ΔS) (Figure App1):

$$P = Q + E + \Delta S \quad [1]$$

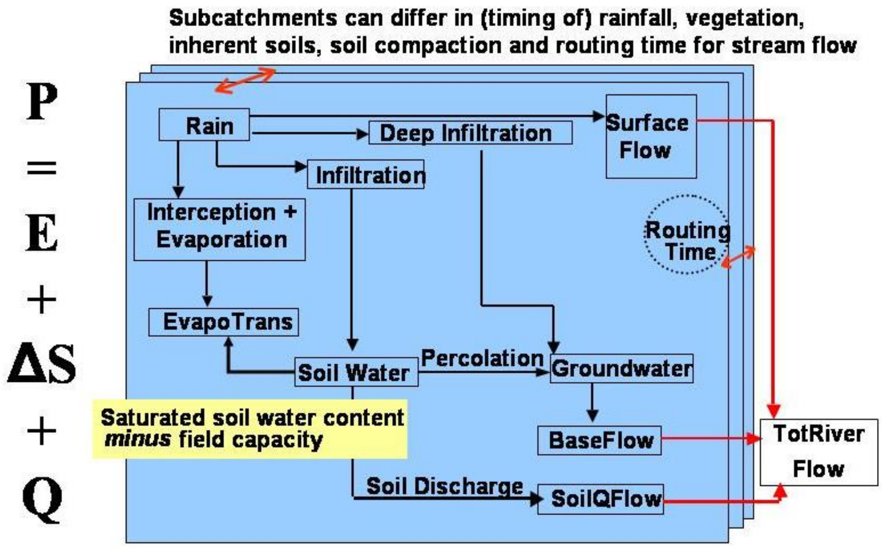

Figure App1.Overview of the GenRiver model

The model may use measured rainfall data, or use a rainfall generator that involves Markov chain temporal autocorrelation (rain persistence). The model can represent spatially explicit rainfall, with stochastic rainfall intensity (parameters RainIntensMean, RainIntensCoefVar in Table 2) and partial spatial correlation of daily rainfall between subcatchments. Canopy interception leads to direct evaporation of an amount of water controlled by the thickness of waterfilm on the leaf area that depends on the land cover, and a delay of water reaching the soil surface (parameter RainMaxIntDripDur in Table 2). The effect of evaporation of intercepted water on other components of evapotranspiration is controlled by the InterceptEffectontrans parameter that in practice may depend on the time of day rainfall occurs and local climatic conditions such as windspeed)

At patch level, vegetation influences interception, retention for subsequent evaporation and delayed transfer to the soil surface, as well as the seasonal demand for water. Vegetation (land cover) also influences soil porosity and infiltration, modifying the inherent soil properties. Groundwater pool dynamics are represented at subcatchment rather than patch level, integrating over the landcover fractions within a subcatchment. The output of the model is river flow which is aggregated from three types of stream flow: surface flow on the day of the rainfall event; interflow on the next day; and base flow gradually declining over a period of time. The multiple subcatchments that make up the catchment as a whole can differ in basic soil properties, land cover fractions that affect interception, soil structure (infiltration rate) and seasonal pattern of water use by the vegetation. The subcatchment will also typically differ in "routing time" or in the time it takes the streams and river to reach any specified observation point (with default focus on the outflow from the catchment). The model itself (currently implemented in Stella plus Excel), a manual and application case studies are freely available (http://www.worldAgroforestry.org/output/genriver-generic-river-model-river-flow ;van Noordwijk et al., 2011).

Appendix 2. Watershed-specific consequences of the land use change scenarios

The generically defined land use change scenarios (Table 4) led to different land cover proportions, depending on the default land cover data for each watershed, as shown in Figure App2.

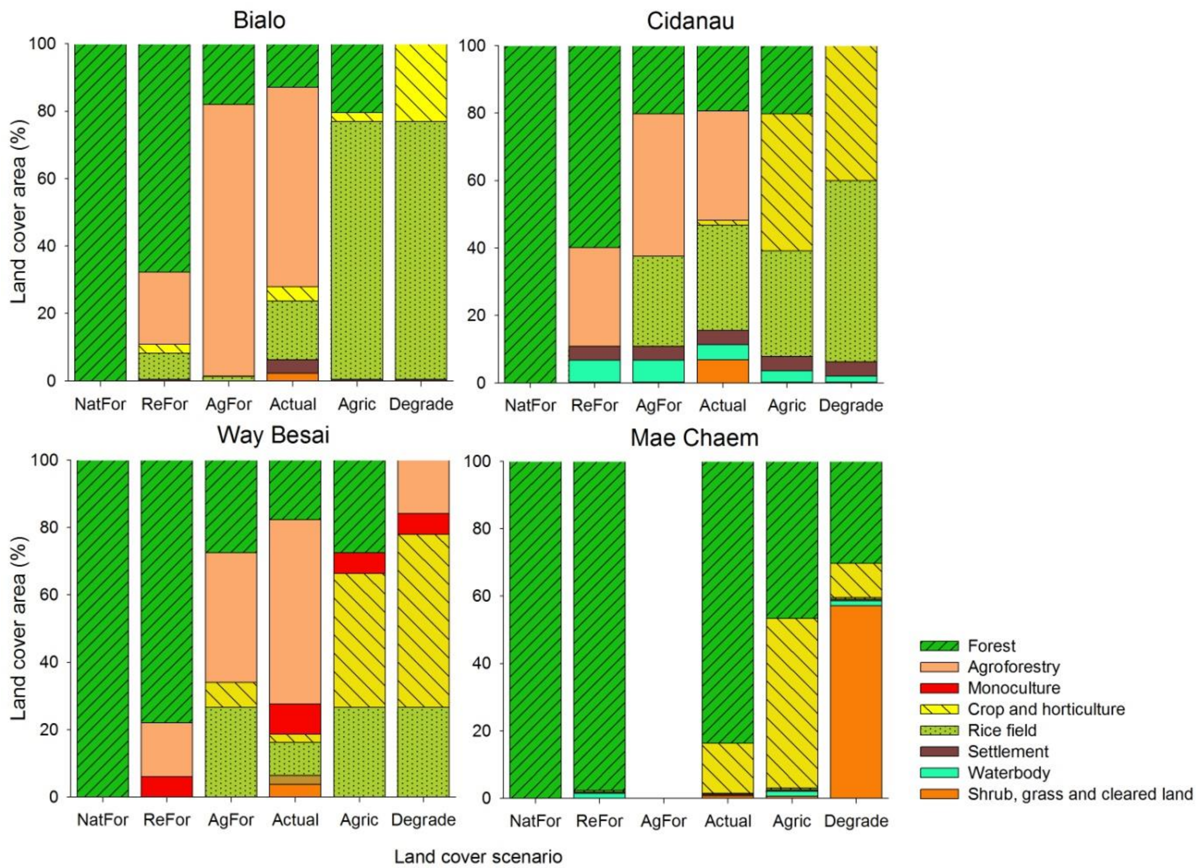

Figure App2. Land use distribution of the various land use scenarios explored for the four watersheds (see Table 4)

Appendix 3. Example of a macro in R to estimate number of observation required using bootstrap approach.

```
#The bootstrap procedure is to calculate the minimum sample size (number of observation) required
#for a significant land use effect on Fp
#bialo1 is a dataset contains delta Fp values for two different from Bialo watershed

#read data
bialo1 <- read.table("bialo1.csv", header=TRUE, sep=",")

#name each parameter
BL1 <- bialo1$ReFor
BL5 <- bialo1$Degrade

N = 1000 #number replication

n <- c(5:50) #the various sample size

J <- 46 #the number of sample size being tested (~ number of actual year observed in the dataset)

P15= matrix(ncol=J, nrow=R) #variable for storing p-value
P15Q3 <- numeric(J) #for storing p-Value at 97.5 quantile

for (j in 1:J) #estimating for different n

#bootstrap sampling
{
for (i in 1:N)
{
#sampling data
S1=sample(BL1, n[j], replace = T)
S5=sample(BL5, n[j], replace = T)

#Kolmogorov-Smirnov test for equal distribution and get the p-Value
KS15 <- ks.test(S1, S5, alt = c("two.sided"), exact = F) P15[i,j] <- KS15$p.value
}

#Confidence interval of CI
P15Q3[j] <- quantile(P15[,j], 0.975)

}

#saving P value data and CI
```

```
write.table(P15, file = "pValue15.txt") write.table(P15Q3, file = "P15Q3.txt")v
/
```