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Discussions

Statistical analysis and modelling of surface runoff from arable fields

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Abstract

Surface runoff generation on arable fields is an important driver of (local) flooding, on-site and off-site damages by erosion, and of nutrient and agrochemical transport. In general, three different processes generate surface runoff (Hortonian runoff, saturation excess runoff, and return of subsurface flow). Despite the developments in our understanding of these processes it remains difficult to predict, which processes govern runoff generation during the course of an event or throughout the year, when soil and vegetation on arable land are passing many states. We analysed the results from 317 rainfall simulations with a resolution of 14286 runoff measurements to determine temporal and spatial differences in parameters governing surface runoff, and to derive and test a statistical model of surface runoff generation independent from an a priori selection of modelled processes types. Measured runoff was related to 20 time-invariant soil properties, three variable soil properties, four rain properties, three land use properties and many derived variables describing interactions and curvilinear behaviour. In an iterative multiple regression procedure, six of these properties/variables best described initial abstraction and the hydrograph. To estimate initial abstraction, a percentage of stone cover above 10 % and of sand content in the bulk soil were needed, while the hydrograph could be predicted best from rain depth exceeding initial abstraction, rainfall intensity, soil organic carbon content, and time since last tillage. Combining the multiple regressions to estimate initial abstraction and surface runoff allowed modelling of event-specific hydrographs without an a priori assumption of the underlying process. The statistical model described the measured data well and performed equally well during validation. In both cases, the model explained 71 and 58 % of variability in runoff volume and runoff rate (RSME: 5.2 mm and 0.23 mm min^{-1}, respectively). Stone cover was most important for the initial abstraction while time since tillage was most important for the hydrograph. The latter variable is neither taken into account in typical lumped hydrological models (e.g. SCS CN approach) nor in more mechanistic models using Horton, Green and Ampt or Philips type approaches to address infiltration. This

finding should foster a discussion regarding our ability to predict surface runoff from arable land, which seemed to be dominated by agricultural operations that introduce man-made seasonality in soil hydraulic properties.

1 Introduction

Consideration of surface runoff generation processes on arable fields is essential for any sustainable water management due to the large area occupied by arable land in many regions of the world (e.g. 24 % of area in Europe of EU27; EUROSTAT, 2012). Runoff generation is the driver of on-site and off-site damages by erosion processes and of nutrient and agrochemical transport (e.g. Haygarth et al., 2006) into open water bodies especially during local floods (e.g. Evrard et al., 2008). Thus, surface runoff generation on arable land is important for hydrological modelling, especially when water quality is considered.

In general, it is acknowledged that three mechanisms generate surface runoff (Li et al., 2012): (i) unsaturated surface runoff (Hortonian-type runoff), (ii) saturation-excess surface runoff, and (iii) return of subsurface storm flow. Not all excess water generated by these mechanisms contributes to surface runoff because some is stored on the surface as depression storage (infiltrating after rain events) and detention storage (partly running-off after events) (Mohamoud et al., 1990). Moreover, surface runoff partly re-infiltrates along its pathway to the stream network (runon infiltration; e.g. Nahar et al., 2008). Many models are available to address one or more of these mechanisms. These include relatively simple approaches that lump all processes operating along the flow path (e.g. the SCS-Curve Number, Mockus, 1972) or more mechanistic approaches addressing a specific process that creates excess water, like models of the Green and Ampt, Philips or Horton type. The mechanistic models may then be applied in a spatially distributed context including further processes occurring during runoff accumulation (for an extensive model overview see, e.g. Borah and Bera, 2003; Migliaccio and Srivastava, 2007 or the various results from the "distributed

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model inter-comparison project", Smith et al., 2004). Small-watershed scale models dealing with surface runoff and soil erosion from arable land often stick to Hortonian-type surface generation approaches (Assouline and Mualem, 2006; Fiener et al., 2008), assuming that surface sealing during heavy rainfall events dominates runoff generation on partly bare soils. Largerscale models typically use Green and Ampt or Philips approaches assuming that infiltration is governed by a propagating wetting front depending on soil properties within the soil column (e.g. Kale and Sahoo, 2011; Klar et al., 2008). However, as processes dominating infiltration and surface runoff generation may vary inter and intra-annually (Li et al., 2012; Vivoni et al., 2007) and even within an event (e.g. Silburn and Connolly, 1995), it is important to address potential switches between runoff generation mechanisms in advanced modelling approaches (Li et al., 2012; Tian et al., 2012).

Despite the improvements of modelling approaches to address different mechanisms of surface runoff generation simultaneously (e.g. the THREW model, Li et al., 2012), it remains challenging to account for the specific temporal and spatial variability of soil and crop characteristics in agricultural landscapes (Fiener et al., 2011a; Green et al., 2003), which may affect infiltration. This challenge results from the interaction with agronomic decisions dominating the soil-vegetation system by influencing (i) the seasonal variability of soil properties and surface roughness depending on tillage operations and (ii) the associated seasonality of plant growth. The first relates to the mostly texture-based, static estimates of important soil parameters, e.g. porosity, used in many modelling approaches. The second is associated with the seasonality of plant and residue cover potentially protecting the soils from crusting (for a review see Fiener et al., 2011a). Despite the developments in our understanding of processes in specific cases, it remains difficult to predict which processes govern runoff generation while soil and vegetation are passing many states during a crop rotation.

The major objectives of this study were (i) to statistically analyse 317 hydrographs from rainfall simulations carried out on different arable soils with different crops to determine temporal and spatial differences in parameters governing surface runoff during

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rainfall events and (ii) to derive and test a statistical model of surface runoff generation independent from an a priori selection of modelled processes types.

2 Material and methods

2.1 Rainfall simulations

Rainfall simulations were carried out on 209 plots (4 to 22 m long; 1 to 2 m wide; Table 1) located in Central Europe by five different research groups covering a broad variety of soils (developed from loess, sand dunes, moraines, Tertiary and Mesozoic sediments and basement rocks) and crops (long-term bare fallow, different small-grain crops, maize and sugar beet) in different development stages. The data were intensively quality checked and homogenised into one data set (Fiener et al., 2011b) which is freely available (Seibert et al., 2011). Details on the locations, the types of rainfall simulators (all Veejet-nozzle types), plot treatments (e.g. fixed plots vs. moving plots), and measurement conditions used by the different groups are given by Fiener et al. (2011b). This data set comprises 729 rainfall simulations, which partly were carried out in sequences. For this study, we only used the first rains in a sequence (termed dry runs) resulting in 317 runs comprising 14 286 runoff measurements during the rainfall simulations while excluding the measurements during afterflow. The measured runoff was correlated to 20 time-invariant soil properties (e.g. texture), three variable soil properties (e.g. moisture content), four rain properties (e.g. specific kinetic energy), and three land use properties (e.g. plant coverage) (Table 1). Many more independent variables were created from these data through transformations (e.g. logarithms), by using thresholds, and dummy variables for the different crops, crop types, months and seasons or by combining variables. For example, rain depth and specific kinetic energy were used to calculate the total kinetic energy applied by a certain rain depth; texture variables expressed as content in the fine earth fraction, as content in the bulk soil,

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or as concentration per soil volume were combined into new variables like the median grain diameter and its geometric standard deviation.

2.2 Statistical analysis and model development

The selection of any infiltration model makes a fundamental assumption on the underlying runoff generation processes (e.g. crusting vs. infiltration front propagation vs. dominance of preferential flow). Following two different and widely used approaches, we fitted Horton-type equations and Green–Ampt-type equations to the hydrographs. Both infiltration equations were flexible enough to be meaningfully fitted to our data despite their contrasting mechanistic justification. Preliminary results showed that both approaches resulted in nearly identical shapes of the hydrograph and similar efficiencies (R^2 was usually above 0.95 and the root mean squared error (RMSE) below 0.1 $\mathrm{mm\,min^{-1}}$ for both types of equation). Furthermore, we encountered the problem of equifinality (Beven and Binley, 1992) that is that many parameter combinations gave statistically similar good results for the same hydrograph and the same infiltration equation (e.g. the RMSE may only change between 0.032 and 0.035 $\mathrm{mm\,min^{-1}}$ for the same hydrograph while the initial infiltration rate of the Horton model changed by a factor of three and the decay constant changed by a factor of ten).

Since both approaches yielded identical results and we did not want to decide a priori on a specific modelling philosophy, we followed a different, purely statistical approach. We focused and analysed four support points of the hydrographs. These were initial abstraction, defined as rain depth till runoff, and total runoff after 20, 30 and 40 mm of rain (P_a, Q_{P20}, Q_{P30}, Q_{P40}, respectively; Table 2). Support points for lower or higher rain depths narrowed the data set and left only subsets which had very early runoff or where high rain depths were applied. Support points for lower or higher rain, hence, were not used at this stage because this reduced the available range of soils, rains and land uses. For the selected four support points, multiple regressions utilizing soil, rain and land use parameters were developed independently following an iterative approach (e.g. Crawley, 2009) taking likely interactions between parameters and curvilinear behaviour into account. Given that many variables correlate (e.g. texture classes but also variables that were obtained by data transformation) and thus also correlate similarly to the support points, we chose those variables out of similarly efficient variables that were widely available (e.g. avoiding unusual texture classes), meaningful and consistent with current knowledge (e.g. avoiding very narrow texture classes), and did not produce an unrealistic behaviour when extended beyond the range covered by measurements (e.g. avoiding transformations that became very steep beyond the measured range). Further, we avoided overparameterization by calculating the Bayesian Information Criterion (BIC, Kuha, 2004).

Given that some variables were not available for the entire data set (Table 1) and could not be included in the equations developed during successive steps, we calculated the residuals for the respective subsets of data during each step and correlated them to the omitted variables. For example, soil moisture at the very surface or in the plough horizon may likely affect initial abstraction but these variables were not available for all hydrographs; hence, we developed a prediction equation for initial abstraction without considering soil moisture; then, we calculated the residuals of this equation for those hydrographs where the soil moisture was available; these residuals were then correlated with the soil moistures to examine whether soil moisture could explain some of the unexplained variation. Other variables were not considered because none had explanatory power.

The selected support points could be predicted by the same variables (indicating that dominant influences did not change during the different rainfall events), while only the calibration parameters changed depending on rain depth. Hence, the equations of the selected support points were combined in the next step into one equation, in which the parameterisation depends on rain depth. This equation was then finally fitted to all 14 286 runoff measurements of the 317 hydrographs (approximately 1 min time steps).

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2.3 Model and validation

To examine whether the final equation would be transferable to other areas, we followed a split-sampling cross-validation approach by randomly choosing 90 % of the 317 hydrographs to determine the equation parameters; the remaining 10 % of hydrographs were used for model validation. This procedure was repeated ten times assuring that every hydrograph was used once for validation. The split sampling yielded a family of similar equations for all subsets that satisfactorily predicted the validation data (see Sect. 3).

All statistical analyses were carried out using the GNU R version 2.14.0 (R Development Core Team, 2011). Besides R^2 and RMSE we also used the Nash–Sutcliffe efficiency (NSE; Nash and Sutcliffe, 1970) as goodness of fit parameter.

3 Results

3.1 Support points

The initial abstraction P_a ranged from 0.7 mm to 62 mm for the 317 hydrographs but only two of the variables contributed to the explanation of this variation. These were total stone cover exceeding 10 %, $Cov_{stone>10\%}$ (range 0...25 %),!!! which was calculated as $Cov_{stone>10\%} = \max(0; Cov_{stone} - 10)$, and sand content (0.063...2 mm) of the bulk soil, Sa_{tot} (range 2...87 %). With increasing stone cover, time to runoff (and hence initial abstraction) increased, while increasing sand content promoted earlier runoff (Eq. 1):

$$P_a = 16.2 + 1.37 \cdot Cov_{stone>10\%} - 2.52 \cdot \ln(Sa_{tot}). \quad (1)$$

Equation (1) explained 53 % of the variation (RMSE 6 mm) of P_a, while $Cov_{stone>10\%}$ and Sa_{tot} explained 37 and 10 mm of the variation, respectively. The RMSE was rather large (and R^2 low) indicating that initial abstraction was strongly influenced by factors that could not be captured by the available variables. Remarkably, rain intensity, which spanned from 29 to 99 mm h^{-1}, had no influence on initial abstraction ($R^2 = 0.0002$) while it dominated the time to runoff because initial abstraction was reached earlier with increasing rain intensity. Also, soil moisture in the surface soil (0.03 m; range: 2...26 w/w-%) or in the plough layer (range: 8...40 w/w-%), which both may especially influence early runoff, did not improve the prediction of P_a.

Q_{P20}, Q_{P30} and Q_{P40} were all explained best by the same variables, namely rain intensity p, time since tillage TsT and organic carbon content C_{org}. This lead to equations of the type:

$$Q_P = f + g \cdot (p) - h \cdot \ln(\mathrm{TsT}) + k \cdot \ln(\mathrm{TsT})^4 + l \cdot \ln(C_{org}) \qquad (2)$$

where Q_P is runoff volume (mm) at rain depth P (mm), p is rain intensity (mm h^{-1}), TsT is time since tillage (d), C_{org} is carbon content (%) and f, h, k and l are empirical parameters that vary with rain depth P.

In general, the higher p was, the more runoff was observed after a given rain depth because the time available for infiltration decreased. The strongest influence, however, was exhibited by TsT, which usually is not regarded in hydrological modelling. With increasing TsT runoff decreased. For example, runoff after 30 mm of rain was on average 20 mm if the rainfall occurred within less than an hour after tillage, while it was less than 5 mm if the rainfall occurred more than 100 days after tillage. This effect was especially pronounced for short TsT (in the range of few hours to single days) although it lasted even for more than 200 days. This strongly decreasing effect made it necessary to use the logarithm and to use a second term ($\ln(\mathrm{TsT})^4$) in Eq. (2), which compensates some of the term ($\ln(\mathrm{TsT})$) at high TsT. Increasing C_{org} also decreased runoff and again this effect was sub-proportional. Despite the large number of available explanatory variables (Table 1) and the large number of measurements, no further variable improved the runoff prediction. This was especially true for soil physical properties that are commonly assumed to influence runoff (e.g. texture parameters, porosity, and moisture).

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3.2 Hydrograph prediction

Given the identical behaviour of all support points, the constants of Eq. (2) could be optimized for any rain depth P by using all data. This lead to:

$$\begin{aligned} Q_{\mathrm{Pr}} = {} & 2.6 - 3.3 \cdot \ln(P_r) + P_r \cdot [0.6 + 4.3 \times 10^{-3} \cdot p - 7.6 \times 10^{-2} \cdot \ln(\mathrm{TsT}) + 5.0 \times 10^{-6} \\ & \cdot \ln(\mathrm{TsT})^4 - 0.19 \cdot \ln(C_{\mathrm{org}})] \\ & \text{for } P_r > 3.3/[0.6 + 4.3 \times 10^{-3} \cdot p - 7.6 \times 10^{-2} \cdot \ln(\mathrm{TsT}) + 5.0 \times 10^{-6} \cdot \ln(\mathrm{TsT})^4 \\ & - 0.19 \cdot \ln(C_{\mathrm{org}})] \qquad (3) \\ & \text{and } Q_{\mathrm{Pr}} > 0 \\ & \text{else} \\ Q_{\mathrm{Pr}} = {} & 0 \end{aligned}$$

where Q_{Pr} is runoff volume (mm) at rain depth P_r (mm) exceeding initial abstraction given by $P_r = P - P_a$.

The combining of Eqs. (1) and (3) allowed the computation of hydrographs for all 317 events. The calculated hydrographs explained 72 % of the variability of the measured runoff volumes (RMSE 5.2 mm; NSE 0.71), as compared to 58 % of the variation in runoff rates (RMSE 0.23 mm mm^{-1}; NSE 0.56). The error distributions (Fig. 1) showed a pronounced excess kurtosis, indicating that the errors were usually less than half as indicated by the RMSEs with the exception of some hydrographs that were poorly predictable. We checked these hydrographs and the corresponding experimental descriptions but found no anomalies that could explain the behaviour of these hydrographs. It is important to note that RMSEs also account for sampling errors associated with field measurements and for inconsistencies among research groups that contributed to the combined data set. Random errors during measurements of runoff rates partly explained the lower performance of modelled runoff rates as compared to runoff volumes. The random scatter in measured runoff rates along a single hydrograph typically was $\pm$ 0.1 mm mm^{-1} (Fig. 2) or half of the overall RMSE. Such random errors and biases are

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more difficult to identify (e.g. errors in plot size determination) and cannot be captured by any model. It is hence unlikely that another equation could explain the hydrographs better.

Examples of measured and predicted hydrographs selected to be close to the mean RMSE are given in Fig. 2. They show rainfall simulations on a long-term bare fallow soil, kept under seed-bed conditions, that was rained on six times during three years. Among the six hydrographs, Fig. 2f exhibits much higher final runoff rates. This illustrates the large influence of TsT as this hydrograph was obtained only one hour after tillage while the other hydrographs were obtained 3 to 5 days after tillage. Despite near constant soil, plot and rain properties for some of the other hydrographs (e.g. D and E, except for the fact that more rain was applied in the case of E), there were differences for which no explanation exists and which hence can also not be captured by the model. Despite this, the model with only five parameters explained all hydrographs reasonably well even though three parameters ($\mathrm{Cov}_{\mathrm{stone}>10\%}$, $\mathrm{Sa}_{\mathrm{tot}}$, and C_{org}) were held constant because they were determined only once on this plot.

The sensitivities of the variables within the complete model were analysed by changing the values of each variable within its measured range (Table 1), while rainfall depth increased from 0 to 60 mm and the other variables were held constant at their mean values (Figs. 3 and 4). With increasing sand content, runoff started earlier (Fig. 4) but the effect was small and most prominent for small sand contents (approximately 0 . . . 10 %; Fig. 3). Stone cover had a much larger effect on runoff initiation and hence on runoff depths (Figs. 3 and 4). Increasing stone cover increasingly retarded runoff but this became effective only above a threshold of 10 % stones (Fig. 3). Consequently, stone cover can be neglected for many soils because the average stone cover in our data set was 6.6 %. Importantly, sand content and stone cover influenced the whole hydrograph (Fig. 4) beyond the start of runoff due to the fact that Eq. (1) was needed to calculate Eq. (3).

With increasing rainfall intensity, runoff rates and volumes increased as predicted by Eq. (3). This also influenced the start of runoff. Runoff started slightly later with

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decreasing rain intensity (Fig. 4) even though intensity was not part of Eq. (1). This is because the influence of intensity on initial abstraction was rather weak when compared to the random scatter of initial abstraction. Using all runoff measurements, as in Eq. (3), instead of using only one data point (initial abstraction) reduced the random scatter and thus this influence became visible in the final Eq. (3). Thus, Eq. (1) was not sufficient to calculate the start of runoff and so was used as an intermediate step in the development of Eq. (3). The same behaviour was true for all other variables that additionally entered Eq. (3).

The influence of C_{org} was of similar strength as rainfall intensity. Runoff rates and volumes decreased with increasing C_{org} (Fig. 3) and caused the runoff to start later (Fig. 4). TsT was about 30 % stronger than C_{org} and rainfall intensity (compare final ranges of runoff volume and rate) but this was an effect of the very short TsT (minimum: 1 h) that were possible with small plots and artificial rainfall but which will unlikely occur on larger fields that need considerably longer than 1 h for tillage. Considering the range of time relevant for whole fields, the influence of TsT was similar in strength as the other influences. The change during the first 12 d after tillage was about the same as the change occurring during the following 215 d (Fig. 4).

3.3 Model validation

The restricted data sets of the split-sampling cross-validation led to similar models as those using the full dataset. The prediction quality did not differ between the calibration and the validation data sets for both runoff volume and rate (Table 3) indicating that the split-sampling models were equally suitable for predictions. The models explained the validation data with a NSE between 0.55 and 0.71 (Table 3, Fig. 5). Runoff volume again was modelled more accurately than runoff rate. Runoff varied between 0 and 59 mm and could be predicted with RMSE = 5.2 mm. However, the models performed somewhat weaker for initial abstraction, as mentioned earlier, since P_a is strongly influenced by factors that could not be captured with the available variables. In general, prediction quality increased with rainfall volume and hence surface runoff volume (Fig. 5).

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4 Discussion

4.1 Initial abstraction

In general, initial abstraction showed substantially more random (unexplained) variability than subsequent runoff rates indicating that measurements are more prone to uncertainty. The high variability of initial abstraction under more or less identical plot conditions could have resulted from small random differences; e.g. compaction at the down-slope end of the plot will encourage early runoff or small depressions at the outlet will increase detention storage and hence delay first runoff. Also subjective decisions by the technical staff carrying out the rainfall simulations are necessary when recording the first runoff (whether it starts with the first single drop or the first continuous flow). Hence, when analysed without consideration of the following runoff measurements, initial abstraction was best explained by the combination of only two soil properties, namely $Cov_{stone>10\,\%}$ and sand content (Eq. 1), despite its large variability (Table 2). However, all other variables, which influenced the hydrograph, also affected initial abstraction (Fig. 4) because (at the plot scale) abstraction must become larger the slower the hydrograph rises. The effect of $Cov_{stone>10\,\%}$ most probably resulted from the macropore space under stones created during tillage that can store runoff. The threshold indicated that small stone contents, which usually also are associated with small and rounded stones, did not exhibit this effect. In this case it can be expected that the stones are embedded within the soil matrix. In general, the importance of the variable $Cov_{stone>10\,\%}$ is in line with findings of Poesen et al. (1990), indicating that stones not fully embedded in the surface soil layer typically lead to preferential infiltration of runoff under these stones.

The influence of sand content was opposite to what might be expected (e.g. from the influence of texture in the SCS CN model). Likely, the increasing sand content decreased aggregate stability (Boix-Fayos et al., 2001) and promoted the breakdown of tillage-induced large voids.

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4.2 Hydrograph shape

The hydrographs could be predicted surprisingly well with an interaction of simple rain, soil and land-use parameters despite the large variation in the data set. These were rain depth exceeding initial abstraction, rain intensity, organic carbon content and time since tillage. The importance of rain depth exceeding initial abstraction and rain intensity is obvious and is also important in many other surface runoff estimates.

The influence of C_{org} on hydraulic parameters (e.g. Rajkai et al., 2004; Scheinost et al., 1997) and erosion (Guerra, 1994) has been shown in several studies. Its influence on the hydrograph likely results from (i) a larger aggregate stability (Auerswald, 1995; Tisdall and Oades, 1982), (ii) larger unsaturated hydraulic conductivity, and (iii) higher biological activity (e.g. Anderson and Domsch, 1989; Weigand et al., 1995) especially by earthworms creating more voids for runoff intake (Auerswald et al., 1996). It is important to note that the soils for which these relationships have been specifically quantified by Weigand et al. (1995) and Auerswald et al. (1995, 1996) comprise a large portion of the present data set. It is thus likely that biological activity, earthworm abundance and cross sectional area of biopores, which were available for these soils, would have been good predictors for the entire dataset if they would have been available for all runs. However, given that these parameters are usually not available for prediction, C_{org} is preferable even though it may only influence infiltration indirectly via aggregate stability and biopore cross-sectional area.

More difficult to interpret is the importance of TsT, because this variable is rarely analysed in relation to runoff generation (and is included neither in the lumped CN model nor in any of the mechanistic models). Surface runoff decreased with increasing TsT, while the opposite might be expected from the typically observed decrease in porosity following a number of drying-wetting cycles after tillage (Ahuja et al., 2006; Franzluebbers et al., 1995; Onstad, 1984) and the decrease in detention and depression storage due to a decrease in random roughness with consecutive rainfalls (Zobeck and Onstad, 1987). Several processes are likely at play at different time scales as TsT

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covered nearly four magnitudes (1 h to 227 d; Table 1). (i) On the short-term (several hours after tillage) the fast drying of freshly tilled soil can increase infiltration capacity and stabilize aggregates during drying (Crouch and Novruzi, 1989; Gollany et al., 1991). The latter reduces soil crusting potential and promotes infiltration. (ii) Within several days following tillage, age hardening of the aggregates will take place due to drying (cycles) and due to biological activity. Biological activity produces binding substances, including hyphae that form more and closer bonds between soil particles, causing cementing substances to precipitate at newly-formed particle contacts (Dexter et al., 1988; Kemper and Rosenau, 1984; Schweikle et al., 1974). All of these mid-term processes of soil structure stabilisation potentially prevent soil crusting, which is most important shortly after tillage since soils are not fully covered by growing crops. (iii) In the long run (weeks to months), TsT is probably also a proxy for the development of plant cover, including changes in tilth underneath a cover and the development of connected biopores reaching the soil surface, even though none of the four cover parameters (Table 1) entered any equation. These interpretations have to remain speculative given the little attention TsT has previously attained in runoff studies. To our knowledge, this parameter has only be analysed in respect to aggregate stability and soil erosion where it can exhibit a large effect (e.g. Auerswald, 1993; Auerswald et al., 1994; Caron et al., 1992; Shainberg et al., 1996) but not for runoff generation. Typically this information is not reported in publications which may explain the often large difference in runoff between different studies as well as some of the unexplained scatter within individual studies given the large changes that can happen at short TsT. More attention should be paid to parameters related to tillage practices given the fact that seedbed conditions, which fall into this range, are often analyzed.

It is debatable whether any empirical or mechanistic approach to model surface runoff can be reliably transferred to other sites given the multitude of conceivable influences. As our data set covers a large range of rainfall, topography, soil and land-use properties (Table 1) the results from the validation are encouraging following a statistical approach. The overall RMSE of runoff volume and runoff rate of 5.2 mm and

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0.23 mm mm^{-1}, respectively, probably cannot be lowered markedly by another model because such differences already existed in the data measured in replicated plots (Fig. 2). The differences must be caused either by systematic measuring errors like a wrong rain intensity or by properties that were not measured, and thus would not be available for other types of models (e.g. antecedent sealing, biopore density, biopore connectivity etc.), or typical errors (e.g. in rain intensity determination or by unresolved spatial variability of soil properties).

5 Conclusions

The large data set of 317 rainfall simulations (14 286 runoff measurements) represented a wide range of arable soils and crops. Runoff measurements were related to 20 time-invariant soil properties, three variable soil properties, four rain properties, three land use properties and derived variables. In an iterative multiple regression procedure six of these properties/variables best described initial abstraction and the hydrograph. The percentage of stone cover above 10 % and the percentage of total sand in the fine earth fraction were needed to estimate initial abstraction, while the hydrograph could be predicted from rain depth exceeding initial abstraction, rainfall intensity, C_{org}, and time since last tillage TsT. The resulting model predicted event hydrographs without a priori assumptions of the underlying process (e.g. Hortonian vs. saturation runoff generation). Validating this approach by creating a family of models by split-sampling, cross-correlation indicated that these models explained 72 % of variability in runoff volume and 58 % of runoff rate (RSME: 5.2 mm and 0.23 mm mm^{-1}, respectively) of the training data and also of the validation data.

Stone cover was most important for the initial abstraction while TsT was most important for the hydrograph. These variables are neither taken into account in typical lumped hydrological models (e.g. SCS CN approach) nor in more mechanistic models using Horton, Green and Ampt or Philips type approaches to address infiltration. This finding should foster a discussion regarding our ability to accurately model surface runoff from arable land, which seemed to be dominated by agricultural operations introducing a man-made seasonality to soil hydraulic properties.

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Table 1. List of rain, plot, soil and land use parameters used to explain runoff hydrographs; all soil properties were determined for the plough horizon (approximately 0–0.3 m), if not otherwise indicated. The availability of each variable relative to the total number of runs ($n = 317$) in percent (%-available) is also given.

Variable (Abbreviation)	Description	Unit	Range	%-available
p	Rain intensity	mm h^{-1}	31...99	100
P_{tot}	Total rainfall applied during simulation	mm	31...99	100
eP	Specific kinetic energy	J m^{-2} mm^{-1}	12...20	100
length	Length of the simulation plot	m	4...22	100
width	Width of the simulation plot	m	1...2	100
slope	Slope of the simulation plot	%	1.6...23.6	100
Cl_{tot}	Total clay content (0...2 µm) in BS[a] (w/w)[b]	%	4...61	100
Si_{tot}	Total silt content (2...63 µm) in BS (w/w)	%	6...86	100
Sa_{tot}	Total sand content (63...2000 µm) in BS (w/w)	%	2...87	100
C_{org}	Soil organic carbon content in FEF[c]	%	0.5...3.5	100
pH	pH	–	4.5...7.5	80
skeleton	Stone (2...200 mm) content in BS (w/w)	%	0...63	100
BD	Air-dry bulk density	kg m^{-3}	1070...1750	42
d_g	Geometric mean particle diameter[d] of BS	µm	1...737	100
vfSi	Very fine silt (2...6.3 µm) in BS (w/w)	%	0...21	100
fSi	Fine silt (6.3...20 µm) in BS (w/w)	%	1...33	100
mSi	Medium silt (20...36 µm) in BS (w/w)	%	1...31	100
cSi	Coarse silt (36...63 µm) in BS (w/w)	%	1...35	100
vfSa	Very fine sand (63...100 µm) in BS (w/w)	%	0...19	100
fSa	Fine sand (100...200 µm) in BS (w/w)	%	0...49	100
mSa	Medium sand (200...630 µm) in BS (w/w)	%	0.4...61	100
cSa	Coarse sand (630...2000 µm) in BS (w/w)	%	0...35	100
vfSt	Very fine stones (2...6.3 mm) in BS (w/w)	%	0...31	100
fSt	Fine stones (6.3...20 mm) in BS (w/w)	%	0...16	100
mSt	Medium stones (20...63 mm) in BS (w/w)	%	0...16	100
cSt	Coarse stones (63...200 mm) in BS (w/w)	%	–	100
Cov_{stone}	Cover by stones	%	0...35	88
θ_{surf}	Volumetric antecedent soil moisture at the surface (0...3 cm depth)	%	2...26	30
θ_{plough}	Volumetric antecedent soil moisture in the plough layer (0...30 cm depth)	%	8...40	20
Crop	Dummy variable of crop type	-	0, 1	100
Cov_{tot}	Total surface cover (cover by either stones, plants or residues)	%	0...93	100
Cov_{veg}	Cover by vegetation	%	0...90	88
Cov_{res}	Cover by residues	%	0...12	88
TsT	Time since tillage	d	0.04...227	100

[a] Bulk soil.
[b] w/w indicates the soil fractions are calculated relative to the total mass of the soil (kg kg^{-1}).
[c] Fine earth fraction.
[d] According to Sinowski et al. (1995).

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Table 2. Runoff variables from the 317 rainfall simulations used for statistical analysis and model development; the number of available data n varies because not all variables were available for all hydrographs.

Variable (Abbreviation)	Description	Unit	Mean	Range	n
t_P	Time to ponding	s	218	29...779	317
t_R	Time to runoff	s	639	63...3119	317
P_a	Initial abstraction, defined as rain depth till runoff	mm	10	0.7...62	317
Q_{P20}	Runoff after 20 mm rainfall	mm	4.1	0... 16.5	317
Q_{P30}	Runoff after 30 mm rainfall	mm	9.3	0... 26.7	317
Q_{P40}	Runoff after 40 mm rainfall	mm	13.4	0... 30.8	176
Q_{tot}	Runoff after total rainfall of an experiment	mm	21.3	0.1... 58.8	317
q	Runoff rate	mm mm^{-1}	0.4	0... 1.2	14 286

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Table 3. Calibration and validation results for all 317 hydrographs used in the split-sampling, cross-validation type of approach; Goodness of fit parameters were calculated based on the full model/data resolution of 1 min; NSE is Nash–Sutcliffe Efficiency (Nash and Sutcliffe, 1970), R^2 is the coefficient of determination, and RMSE is the root mean square error; n indicates the number of single measurements used for calibration and validation.

	Q [mm]		q [mm mm^{-1}]	
	Calibration	Validation	Calibration	Validation
n	128 574	14 286	128 574	14 286
R^2	0.72	0.72	0.58	0.58
RMSE	5.19	5.21	0.23	0.23
NSE	0.71	0.71	0.56	0.55

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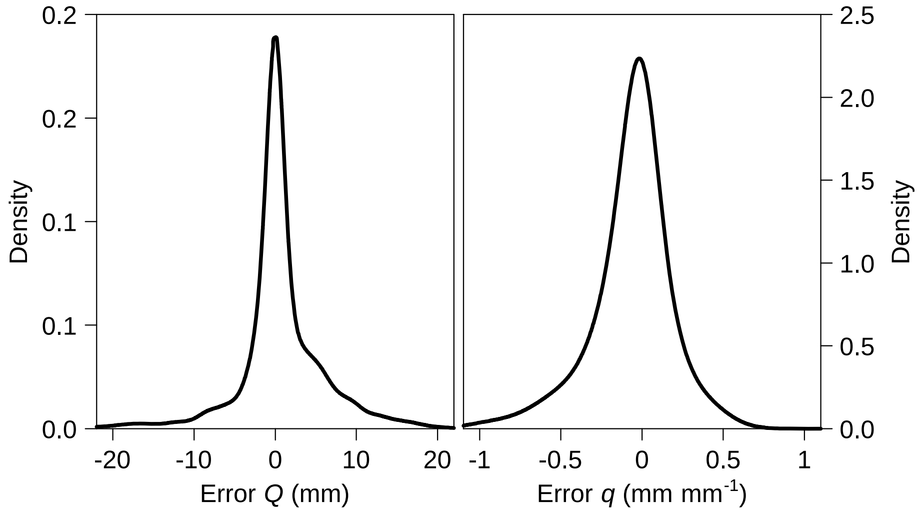

Fig. 1. Error distribution of runoff depth Q and runoff rate q for 14 286 runoff measurements during 317 events.

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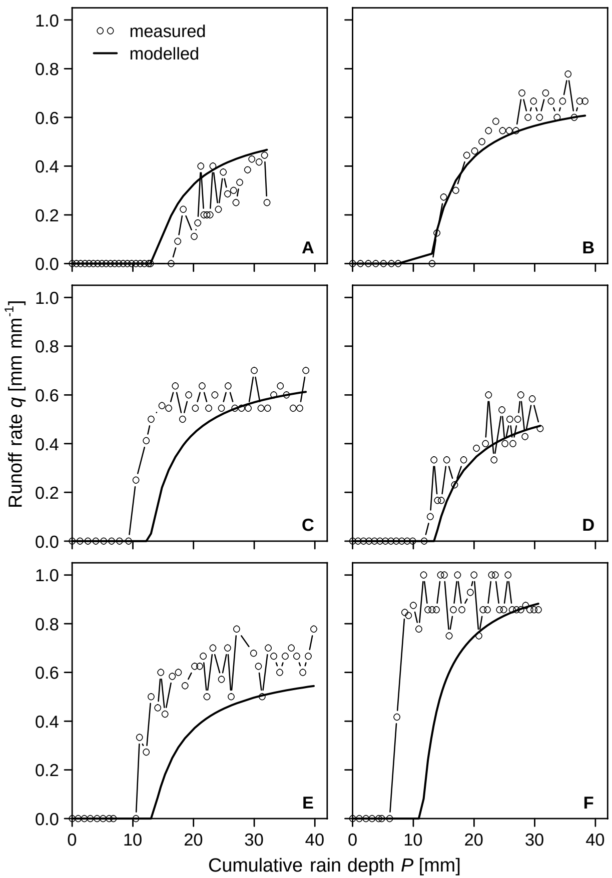

Fig. 2. Examples of runoff rates during six events in different months and years on one plot kept under seedbed conditions. Note: time since tillage is 0.04 d in **(F)**, while it is 3. . . 5 d in all other cases.

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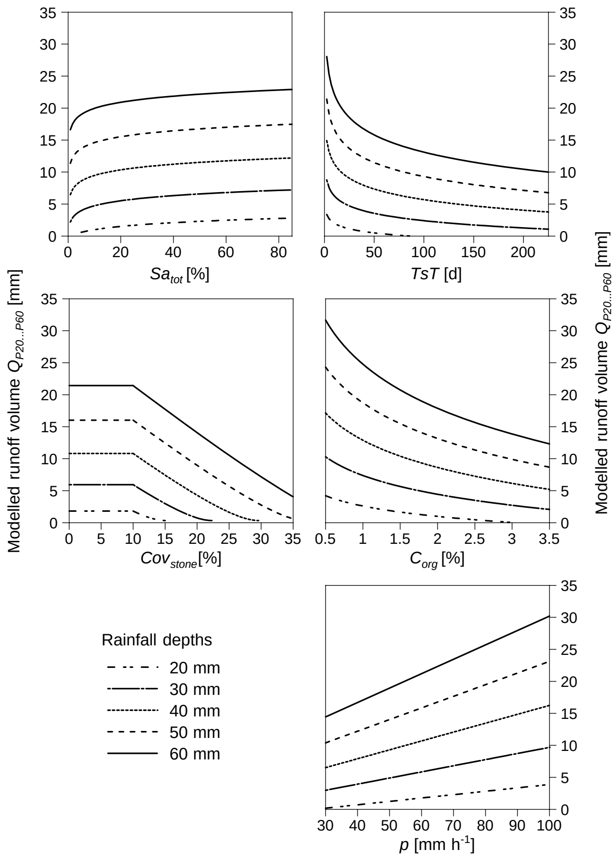

Fig. 3. Modelled runoff volumes ($Q_{P20...60}$) for different rainfall depths (20...60 mm) and varying total sand content Sa_{tot}, stone cover Cov_{stone}, time since tillage TsT, soil organic carbon content C_{org}, and rainfall intensity p as used in Eqs. (1) and (3); for the modelling approach all variables except the one varied were kept constant at their mean value (for values see Fig. 4).

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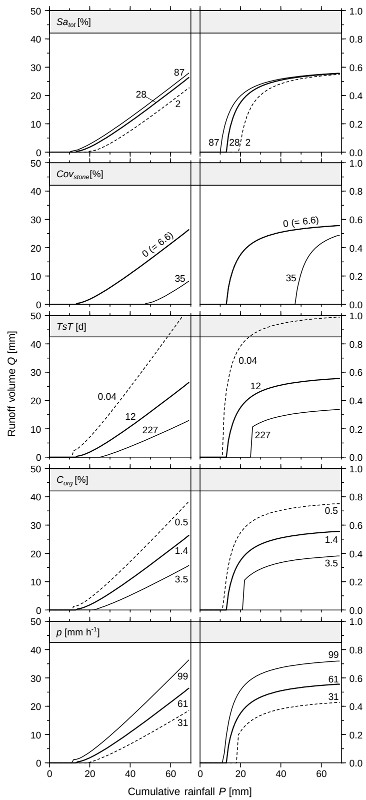

Fig. 4. Modelled runoff volume and runoff rate for mean (bold line), minimum (dotted line), and maximum (thin line) values of total sand content Sa_{tot}, stone cover Cov_{stone}, time since tillage TsT, soil organic carbon content C_{org}, and rainfall intensity p. Numbers denote the minimum, mean and maximum of each variable. All variables were kept constant at their mean value except the one varied. For Cov_{stone} the minimum and the mean result in the same hydrograph as stone cover becomes active only for $Cov_{stone>10\,\%}$.

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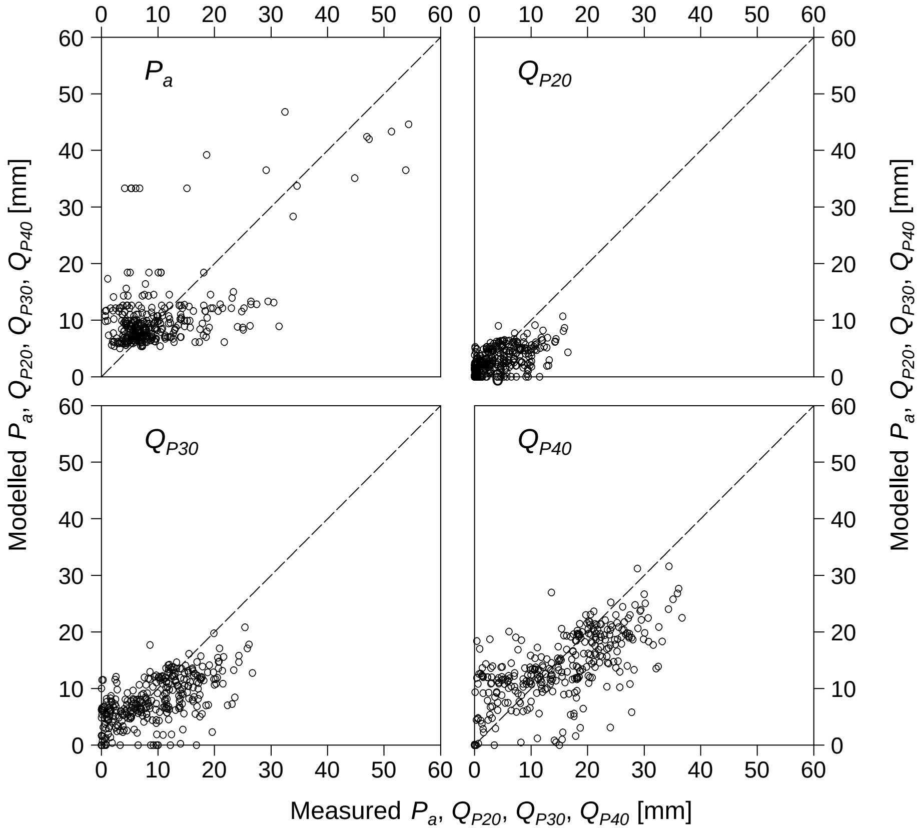

Fig. 5. Modelled vs. measured initial abstraction P_a, runoff after 20, 30 and 40 mm of rainfall, respectively (Q_{P20}, Q_{P30}, Q_{P40}); data shown combine all validation results of the split-sampling, cross-validation type of approach; root mean square errors are 7.0, 3.5, 5.3, and 6.9 for P_a, Q_{P20}, Q_{P30}, and Q_{P40}, respectively.

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