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1 The topographic control on land surface energy
2 fluxes

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10

11 **Abstract**

12 Subsurface hydrodynamics are an important component of the hydrological cycle
13 and a key factor in the partitioning of the land surface energy fluxes. Because
14 also of computational reasons they are often neglected, or strongly simplified, in
15 numerical weather prediction and climate models. Particularly in regions where
16 the water table is shallow, soil moisture acts as a link between land, atmosphere
17 and groundwater and, because of its long-term memory represents a buffer for
18 the effects of climate variability. To dynamically model this system we couple
19 a variably saturated groundwater flow model (ParFlow) with a surface model
20 (CLM). In order to overcome the computational limitations of such an explicit
21 representation of the groundwater dynamics, we propose an approach for the
22 statistical correction of the bias of the energy fluxes of a simple scheme, based
23 on the comparisons with fully-coupled subsurface-land-atmosphere simulations.
24 This simple dynamical scheme computes the potential latent heat flux in case
25 of near saturation. In particular, we focus on the ability of topography-related
26 indices, such as the topographic wetness index and the depth-to-water index,
27 to provide information on the availability of water for evapotranspiration. The
28 topographic indices confirm to be good predictors for the moisture availability.
29 While the small scale structure cannot be captured well, the results show that
30 the large-scale biases of latent heat flux over the domain are effectively removed.
31 Moreover, the bias corrected fluxes more accurately reproduce the fluxes of the
32 full modelling system than common used free drainage simulations. Thus, the
33 proposed approach can be useful in approximating the effect of groundwater on
34 land surface water and energy fluxes in e.g. regional climate models.

35 1 Introduction

36 Groundwater is the primary source of fresh water (*Gleick, 1993*) and a major
37 source of water supply for consumption, agriculture and industry. As an im-
38 portant element of the hydrologic cycle, groundwater sustains surface waters,
39 ecosystems and the aquatic communities that populate these areas (*Alley et al.,*
40 *2002, Fan and Miguez-Macho, 2010*). In the areas where soil moisture is the lim-
41 iting factor for the evapotranspiration, capillary rise from the groundwater table
42 may result directly into enhanced evapotranspiration (*Anyah et al., 2008*) and
43 decreased infiltration (*Yeh and Eltahir, 2005a*). The water table depth (*wtd*) is a
44 function of groundwater dynamics and surface fluxes, such as evapotranspiration
45 and infiltration in the unsaturated zone (*York et al., 2002*) and affects the soil
46 moisture profile at different space and time scales (*Vergnes et al., 2012*). This is
47 reflected in the partitioning between surface and subsurface soil water and the
48 partitioning between surface sensible and latent heat fluxes, which affects the
49 terrestrial water and energy balance and the atmospheric processes (*Choi and*
50 *Liang, 2010, Leung et al., 2011*).

51 The influence of groundwater storage on the energy and water exchanges
52 between soil and atmosphere can be conceptually understood for an idealized
53 hillslope. The hillslope is assumed to be divided into three regions with deep
54 (*C*), intermediate (*B*) and shallow (*A*) groundwater table (*Kollet and Maxwell,*
55 *2008*). Assuming that the water table follows the topography (a simplification
56 that is generally true for topographically driven groundwater flow), it is deeper
57 for the hill tops and shallower in the valleys, thus the three zones correspond
58 to three conceptual soil columns, that are connected by lateral groundwater
59 flow. In case *A*, where the water reaches or is close to the surface, the surface
60 processes are not water limited and small variations in water table depth do not
61 affect the land surface processes. In case *C*, the water can only drain downwards

62 (groundwater recharge) and there is no significant linkage between water table
63 depth and land surface processes. Finally, in case *B*, which corresponds to the
64 transition between the two regimes, the groundwater is at a “critical depth”, i.e.
65 small changes in depth can alter the water availability for evaporation and root
66 water uptake, allowing the vertical redistribution of soil moisture. This implies
67 that in case *B*, there is a connection between groundwater and land surface
68 related to the location of the water table and, thus, to the availability of water,
69 which affects the energy fluxes (in particular the partition of energy between
70 sensible and latent heat). In this regime it is therefore most important to model
71 the position of the groundwater table and its evolution over time accurately.

72 This subdivision in three regimes was reflected in the relationship between
73 latent heat and depth to groundwater found in simulations (*Soylu et al.*, 2011,
74 *Kollet and Maxwell*, 2008) and was also confirmed in measured data (*Szilagyi*
75 *et al.*, 2013). They show nearly no dependence of the fluxes on *wtd* for deep and
76 shallow water tables (case *A* and case *C*), while for the intermediate region (case
77 *B*) the curve is steep, implying that small changes in groundwater table influence
78 the energy fluxes. The depth of this critical zone is also determined by the plant
79 rooting depth (*Fan*, 2015). While this relationship between energy fluxes and
80 water table depth is generally present in the critical zone, its strength can vary,
81 depending on the soil composition and the land use type (*Maxwell et al.*, 2007,
82 *Kollet and Maxwell*, 2008).

83 Despite the importance of groundwater dynamics for climate, the subsurface
84 in *LSMs* is commonly represented by single soil columns. Moreover, a free
85 drainage boundary condition at the bottom of the column is often used, which
86 implies a negligible upward diffusive flux (*Yeh and Eltahir*, 2005b), even for
87 regions of the domain where the water table is shallow in reality. This means
88 that the lateral movement of water between the columns is neglected and water

89 is lost, instead of being laterally distributed towards the neighbouring columns,
90 causing a bias in the mass and energy balance (*Tian et al., 2012, Miguez-Macho*
91 *et al., 2007*).

92 In the last decades a number of studies, which are briefly reviewed be-
93 low, demonstrated the importance of subsurface hydrodynamics for climate and
94 weather modelling. The Land Surface Models (*LSMs*) provide the lower bound-
95 ary condition for temperature and moisture in the General Circulation Models
96 (*GCMs*), the mesoscale Regional Climate Models (*RCMs*) and the Numerical
97 Weather Prediction models (*NWPs*). They describe the water and energy
98 fluxes on the land surface, and the partitioning of the incoming precipitation
99 into surface and subsurface runoff, evapotranspiration (*ET*) and soil moisture
100 variation, but their description of the subsurface hydrodynamics is often highly
101 simplified (*Tian et al., 2012*). Several studies on the coupling of a groundwater
102 component in *LSMs* showed that the inclusion of a dynamical representation of
103 water table modifies the vertical profile of soil moisture and improves the wa-
104 ter budget simulation (e.g., *York et al., 2002, Maxwell and Miller, 2005, Jiang*
105 *et al., 2009, Lo and Famiglietti, 2011, Leung et al., 2011*). Over short time scales
106 and at the catchment scale, *Maxwell et al. (2007)* showed that a more realis-
107 tic soil moisture distribution is obtained with the inclusion of the groundwater
108 and that this affects the local atmospheric convection. *Miguez-Macho et al.*
109 *(2007)* showed that the presence of the water table as the lower boundary of the
110 soil causes a slower vertical drainage, that concurs with the upward capillary
111 flux and the lateral groundwater convergence to the increase of soil moisture in
112 the root zone, compared to a free-drainage run. In areas where the water table
113 is deep, variations in land surface energy fluxes mostly depend on the precipita-
114 tion (*Maxwell and Kollet, 2008*) and the free (gravity) drainage assumption is
115 reasonable, since the saturated and unsaturated zones of the subsurface are not

116 interacting (*Vergnes et al.*, 2014, *Lo and Famiglietti*, 2010). When the water
117 table is shallow, which is the case for almost 50% of the global land accord-
118 ing to simulations (*Koirala et al.*, 2014), the upward flux from the aquifer to
119 the shallow soil compartment and the decrease in infiltration (*Yeh and Eltahir*,
120 2005b) affect the seasonal precipitation and temperature (*Jiang et al.*, 2009,
121 *Anyah et al.*, 2008, *Maxwell and Kollet*, 2008, *Betts*, 2004).

122 In a study on the strength of the interactions between land and atmo-
123 sphere, *Lo and Famiglietti* (2011) found that the effect of the groundwater on
124 precipitation varies globally. In areas where the subsurface and atmosphere
125 are strongly coupled, the groundwater presence enhances shallow soil moisture,
126 which is transported vertically via evapotranspiration, impacting the initiation
127 of convection. The augmented precipitation induces a positive feedback, where
128 the wetter soil produces more evapotranspiration. Therefore, wet areas may get
129 wetter and arid regions may get drier (*Chou and Neelin*, 2004). In reality, this
130 rule of thumb for the expected trend in climate change is, however, extremely
131 reductive and evidence of the opposite trend has been found, especially on land
132 surfaces (*Greve et al.*, 2014).

133 In a comparison of two runs of a regional model with and without aquifer over
134 a catchment in northeastern Kansas, *York et al.* (2002) found that between 5%
135 and 20% (for wet and dry years, respectively) of ET comes from the aquifer. In
136 a similar fashion, *Niu et al.* (2007) compared two experiments with free drainage
137 and groundwater recharge as lower boundary condition, finding that the latter
138 produces 4% to 16% (depending on the region) more annual evapotranspiration,
139 with the transitional arid-to-wet areas presenting the largest effect of wetter soil
140 on ET . Especially during dry periods, a shallow water table can sustain ET and
141 reduce the sensitivity of surface soil moisture to precipitation anomalies (*Vergnes*
142 *et al.*, 2014, *Yeh and Eltahir*, 2005a). Conversely, in areas with deeper ground-

143 water table the soil moisture is more sensitive to anomalies in precipitation,
144 which result in stronger fluctuations in the evaporative fraction (*Leung et al.*,
145 2011).

146 The variations in the fluxes of energy and moisture affect precipitation (*Anyah*
147 *et al.*, 2008) directly through convection or indirectly through advection, en-
148 creasing the spatial scale of the influence of groundwater on the atmosphere (*Yuan*
149 *et al.*, 2008). According to *Lam et al.* (2011), groundwater can locally contribute
150 more than 30% of evaporation in summer and increase the multi-year memory
151 of climate models, by a sustained influence of wet episodes for several years.
152 The water table acts as a buffer for the temporal variations of the soil moisture,
153 due to its slow changing nature (*Miguez-Macho et al.*, 2007, *York et al.*, 2002)
154 and reduces the impact of drought in forested regions (*Decker et al.*, 2013).
155 As the atmospheric forcing propagates through the land surface hydrologic cy-
156 cle, its anomalies persist in the water table levels, due to the longer memory
157 of groundwater compared to soil moisture; they are then transported upward
158 and impact the future climate (*Yeh and Eltahir*, 2005a). The ability of the
159 land surface to respond to anomalies in the climate is obviously affected by
160 land use change (*Leung et al.*, 2011) and the water table position responds also
161 to the depletion caused by groundwater pumping (*Leng et al.*, 2014), so the
162 anthropogenic influence alters significantly the hydrologic cycle (*Ferguson and*
163 *Maxwell*, 2010).

164 As discussed above, groundwater hydrodynamics are a key factor in influenc-
165 ing the energy fluxes at the land surface, yet a full three-dimensional subsurface
166 representation is computationally not feasible in global climate simulations. To
167 overcome this limitation we propose a Model Complexity Reduction Approach
168 (*MCRA*), connecting a parameterized groundwater representation for large scale
169 models, with small-scale physics based simulations. In the MCRA most of the

170 surface physics is modelled by a dynamical model and bias-corrected with a
171 simple statistical model. The reverse approach was used for fast and accurate
172 modelling radiative transfer in atmospheric models (*Venema et al.*, 2007; *Man-*
173 *ners et al.*, 2009; *Schomburg et al.*, 2012). In these radiative transfer schemes,
174 the simpler physical or statistical model was responsible for efficiently modelling
175 the small-scale variability, while the complex physical model was used to reduce
176 biases.

177 The approach is based on two sets of simulations. A full-physics simulation,
178 *CplxRun*, represents the virtual reality, while a highly parameterized simulation,
179 *LandParm*, is used as a reference. For this study, a Potential Latent Heat Run
180 (*PotLERun*) is used as parameterized simulation. In it, the water table depth
181 is fixed at the soil surface, as opposed to the *CplxRun*, where the water table is
182 free to move in response to atmospheric forcing and topographic characteristics.

183 Topographic indices, such as Depth-To-Water and Topographic Index, ef-
184 fectively represent the relative abundance of water at different locations in the
185 watershed. Based on the fact that evapotranspiration is constrained by the
186 availability of water and radiation, we will develop a statistical model for the
187 correction of the *PotLERun*, in order to approximate the results of the *CplxRun*.
188 The validity of the concept and the ability to correct the latent heat flux will
189 be demonstrated using cross-validation in space.

190 The paper is structured as follows: in the first part we present the method-
191 ology. The Model Complexity Reduction Approach is described as a general
192 concept, followed by the simulations that this work is based on are then il-
193 lustrated, starting with the model used to perform them. In section 2.4 the
194 topographic indices used in the bias correction are presented and the sensitiv-
195 ity of the latent heat flux to these indices and to other static parameters is
196 shown. Finally, the statistical bias-correction model is explained, tested in a

197 cross-validation and compared to a free drainage simulation.

198 2 Methodology

199 In this section, we present the Model Complexity Reduction Approach, the
200 adaptive parameterization that is the core of this work. We then introduce the
201 simulation data, starting from the numerical model used to obtain them (Sec-
202 tion 2.2). The general characteristics of the domain are presented in Section 2.3,
203 with a particular focus on possible key parameters for a statistical model for
204 energy and moisture fluxes. The data originate from a previous study, *Rahman*
205 *et al.* (2014), where more details can be found.

206 2.1 Model Complexity Reduction Approach, MCRA

207 A Model Complexity Reduction Approach (*MCRA*) is proposed (Figure 1),
208 where a fast simplified model (*LandParm*) is run over the whole domain. Be-
209 cause of the simplifications, LandFast is biased. These biases are corrected
210 statistically (bias corrector). The biases are estimated by comparing LandFast
211 output to the results of a full complex model system (*LandCplx*) simulations.
212 In the *Updater* all the information is collected and elaborated, in order to provide
213 the updated values of spatially averaged latent heat, serving as lower boundary
214 flux for *GCMs* and *RCMs*. The information is represented by static parameters
215 used as predictors and the results of the full complex model system (*Landcplx*)
216 simulations.

217 In this study the *MCRA* adaptive approach is implemented using a LandFast
218 simulation where the water table was fixed at the surface and the source/sink
219 term turned off, to simulate a full availability of moisture (Potential Latent Heat
220 Run, *PotLERun*), while the rest of the setup (e.g., resolution) is identical to the
221 Complex Run. Because the soil is saturated, the computationally expensive

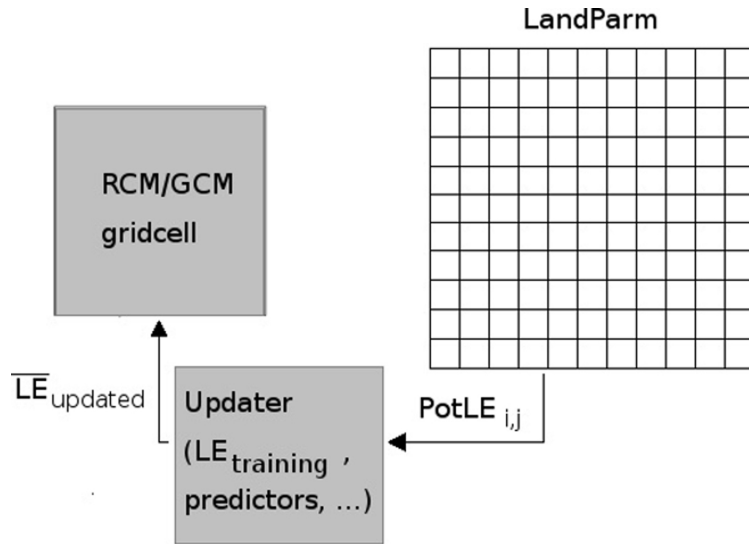


Figure 1. Scheme of the MCRA concept.

222 flow of water does not need to be simulated. This allows a reduction in the run
 223 time, that is estimated to be 1/15 of the standard run time for *CplxRun*.

224 The data for training the scheme are produced by a Complex Run (*CplxRun*),
 225 where the subsurface hydrodynamics is fully simulated and the water table is
 226 free to move.

227 We will develop a statistical model for the difference between *CplxRun* and
 228 *PotLERun* to function as the updater. Because *PotLERun* already includes
 229 much physics, the statistical model can be much more parsimonious than a
 230 full statistical model for the surface fluxes, and only focuses on correcting for
 231 the over abundance of soil moisture. Since the *PotLERun* does not provide a
 232 physically consistent water table depth, the topographic indices, that are proxies
 233 of the wetness of the soil, are used as predictors in the statistical model for the
 234 difference in evapotranspiration between the two runs, ΔLE .

235 The advantage offered by the use of simulations instead of measurements
 236 is the full availability of hourly data for the variables and full control on the

237 static parameters. The goal of this study is thus to develop a fast surface
 238 parameterisation that mimics LandCplx as well as possible.

239 For each class, the behaviour is assumed to be consistent and on average
 240 the same in the validation and in the training set. The predicted value for the
 241 latent heat, $LE_{pred,i}$, in each cell i of the class is calculated as the difference
 242 between the value of $LE_{pot,i}$ and the corresponding ΔLE , δ_i :

$$LE_{pred,i} = LE_{pot,i} - \delta_i \quad (1)$$

243 The value of δ_i is unknown during the prediction phase. It is approximated
 244 with the average ΔLE of the same class, as calculated in the training set, $\overline{\delta_{train}}$:

$$LE_{pred,i} = LE_{pot,i} - \overline{\delta_{train}} \quad (2)$$

245 In this way the error in the prediction for each cell is equal to the difference
 246 between the true value of ΔLE in the cell and the mean value of it for that
 247 class. The bias is then:

$$\overline{(LE_{pred,i} - LE_{true,i})} = \overline{(\delta_i - \overline{\delta_{train}})}, \quad (3)$$

248 meaning that if the residuals of the ΔLE values are homogeneously distributed,
 249 the bias will be small and the spatial mean of predicted latent heat will be a
 250 good approximation of the true value.

251 2.2 ParFlow.CLM

252 *ParFlow* is a variably saturated groundwater flow model with an integrated
 253 overland flow simulation capability. It has been coupled with *CLM* (Common
 254 Land Model) to incorporate physical processes that are related to the balances
 255 of energy and water at the land surface (*Maxwell and Miller, 2005, Kollet and*

256 *Maxwell*, 2006, 2008). *CLM* calculates the mass and energy balance at the land
257 surface, in terms of evaporation from canopy and ground surface, transpiration
258 from plants, ground heat flux, freeze-thaw processes and sensible heat fluxes.
259 *ParFlow* replaces the soil column formulation and runoff scheme of *CLM*. The
260 coupling between the two models is performed via soil moisture, evapotranspi-
261 ration and infiltration of water. The atmospheric forcing can be represented by
262 reanalysis data or the results from an atmospheric model.

263 **2.3 The simulations**

264 The analysis deals with the results of two *ParFlow.CLM* simulations (from now
265 on, the *CplxRun* and the *PotLERun*) performed over a domain that includes
266 the Rur catchment (*Rahman et al.*, 2014). The spatial resolution is $\Delta x = \Delta y =$
267 1 km and the domain includes 168×168 cells. The soil is subdivided in layers,
268 the thickness of which is increasing with depth (it varies from 0.04 m for the
269 uppermost layer, to 4 m for the deepest one) in order to better resolve the
270 dynamics in the shallow subsurface. The outputs consist of two-dimensional
271 hourly data for the energy fluxes at the surface and three-dimensional hourly
272 data for saturation and pressure in the subsurface, that span one year (namely
273 2009). The water table depth is calculated based on the pressure profile in the
274 subsurface, for each cell in the domain and each time step of the simulation.
275 Positive values indicate cells where the groundwater table is below the surface,
276 while negative values correspond to ponded water. The depth varies in time in
277 response to the atmospheric forcing (*Rahman et al.*, 2014) and in space according
278 to the hydraulic properties, gravity and pressure driven fluxes.

279 The domain encompasses a variety of land uses and soil textures (Figure 2).
280 The land use classification follows the GLC2000 dataset (*Skalsky et al.*, 2009).
281 The domain shows a large area of mostly natural vegetation in the southern

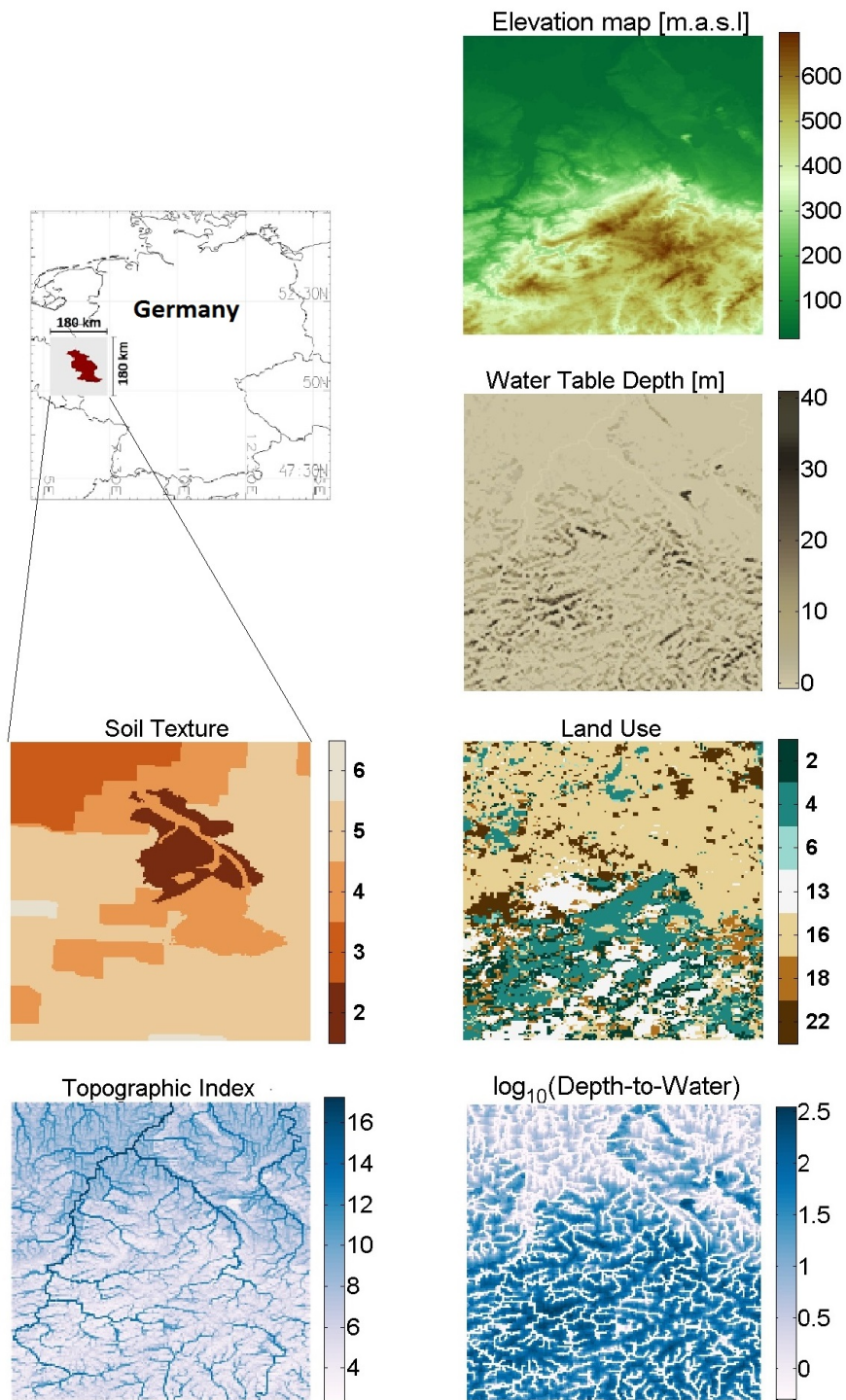


Figure 2. Overview of the topographic and surface characteristics of the domain. For the land use map, the correspondence is: 2) broadleaved deciduous trees; 4) needle-leaved evergreen trees; 6) mixed leaf type trees; 13) herbaceous cover; 16) cultivated and managed areas; 18) mosaic: cropland/shrub or grass cover; 22) artificial surfaces and associated areas. For the soil texture, the correspondence is: 2) silty clay; 3) loamy sand; 4) silt loam; 5) clay loam; 6) silt.

282 mountainous part, in correspondence to the Eifel National Park, while the north-
283 ern part is mostly covered by cultivated and managed areas. With regard to the
284 soil texture, silt is only present in two small areas, while clay loam represents
285 the most abundant soil type. Silt loam is present in both the mountainous and
286 the flat areas. Conversely, loamy sand is only present in the flat area. The Rur
287 catchment area mostly presents silty clay in the flat part and silt loam in the
288 mountains.

289 For the first simulation, the *CplxRun*, the subsurface hydrodynamics is al-
290 lowed to vary dynamically, in response to the spatial heterogeneity and the
291 atmospheric forcing. The setup for the second simulation, the *PotLERun*, only
292 differs from the *CplxRun* for the fact that the whole domain is kept close to
293 saturation by prescribing the pressure in the subsurface. The potential evap-
294 otranspiration is defined as “the rate at which evapotranspiration would occur
295 from a large area completely and uniformly covered with growing vegetation,
296 which has access to an unlimited supply of soil water” (*Dingman*, 2002). This
297 is the state which is simulated and which names the PotLERun. It represents
298 a measure of the demand of water from the atmosphere that the soil can fully
299 meet only if it is never water limited, as is the case in this simulation.

300 In this case the *CplxRun* represents the virtual truth, while the *PotLERun*
301 is Landparm, a numerically efficient parameterization providing insight on the
302 behaviour in case of extreme wetness.

303 The area is then split into a training and a validation subset. For the train-
304 ing set, both the results from *CplxRun* and *PotLERun* are used to develop the
305 statistical model. The model is then tested on the validation set, by correct-
306 ing the results of PotLERun, and comparing the corrected values against the
307 *CplxRun* results.

308 **2.3.1 Statistical model**

309 The diurnal cycle on one subset was fitted with a modified Gaussian function,

$$F(t) = A_0 + A * \exp\left[\frac{-(t - t_0)^2}{2 * w}\right] \quad (4)$$

310 using an offset A_0 , the difference between the maximum and minimum values
311 as height A , $t = 13$ as the central hour, t_0 , and a width, w , of 7 hours, for each
312 class of the topographic index. The parameters were estimated by means of a
313 dummy distribution with the same shape as the diurnal cycle over the month
314 of July (where the bell is more pronounced) and checked on the other months.

315 **2.3.2 Validation method**

316 In order to demonstrate the ability of the topographic indices to quantify the
317 ΔLE , the following procedure was applied. The entire domain was subdivided
318 into two subsets, one for the training and one for the validation of the method.
319 For the training data, the information coming from the *PotLERun* and the
320 characteristics of the cells (e.g., the topographic indices) were used as predictors
321 to develop a model for ΔLE . For validation, the outputs of the *CplxRun* were
322 used.

323 The two subsets are organized in a “checkers” scheme (Figure 3), where the
324 dark squares represent the training data and the whites are the validation, and
325 vice versa. To ensure independence, the size of the squares needs to be large
326 enough, thus the correlation length of the ΔLE was estimated. The analysis of
327 the variogram shows it to be no larger than 5 km, which means that squares of
328 21 km of side length are a reasonable choice.

329 The comparison against a free-drainage (*FD*) simulation (*Rahman et al.*,
330 2016) serves as a second method of validation. In the *FD* simulation, the mois-
331 ture is drained by gravity through the bottom of the domain, as opposed to



Figure 3. Training and Validation set 1 (left) and Training and Validation set 2 (right). The domain is subdivided into two subsets, according to a checkers scheme, that are used as training and validation set.

332 being redistributed in the subsurface according to the slopes. This boundary
 333 condition, commonly applied in land surface models, is known to have a “dry
 334 bias” due to the loss of water from the bottom of the column.

335 2.4 Topographic indices

336 2.4.1 Topographic Wetness Index

337 The *topographic index (TI)*, also called *wetness index*, was introduced in 1979,
 338 in the framework of the TOPMODEL approach (*Beven et al., 1984, Beven and*
 339 *Kirkby, 1979*). It is defined as

$$TI = \ln \left[\frac{\alpha}{\tan \beta} \right], \quad (5)$$

340 where the local slope β [-] is derived from the digital elevation model (DEM)
 341 and the specific catchment area α [m], is the area from which the water drains
 342 through the cell under investigation (contributing area), divided by the contour
 343 length. In equation 5, the slope determines the celerity of the runoff, while the
 344 contributing area is a measure of the potential amount of water. The *TI* rep-
 345 represents an indicator of topographic heterogeneity in the catchment. It provides
 346 general information about shallow groundwater levels, at least in zones where

347 these are mainly determined by topography and, thus, may be an indicator of
348 the availability of water for evapotranspiration. In the last decades, the topo-
349 graphic index has been widely used as an index of hydrological similarity, under
350 the assumption that points of a catchment with the same value of TI behave
351 similarly, from the hydrological point of view (*Beven, 1997*). In summary, the
352 topographic index formulation is based on some general assumptions (*Beven,*
353 *1997, Ducharne, 2009, Franchini et al., 1996*) that are:

- 354 1. the local slope is a good approximation for the hydraulic gradient;
- 355 2. the dynamics of the water table can be approximated by a succession of
356 steady states, in which an immediate balance between the local outflow
357 from the saturated zone and the recharge from the contributing area is
358 achieved at every time step and in every cell; and
- 359 3. the transmissivity of the soil declines exponentially with depth.

360 The validity of these assumptions varies between catchments and climates. If
361 groundwater levels change slowly over time, for example, successive steady states
362 represent the dynamics adequately (*Rinderer et al., 2014*).

363 Alternative and more complex indices have been proposed and used (*Hjerdt*
364 *et al., 2004, Western et al., 1999*), such as the soil-topographic index (*Beven,*
365 *1986*) and the climato-topographic index (*Merot et al., 2003*), which include
366 information about the transmissivity and the volume of annual effective rainfall,
367 respectively. This is mainly necessary when a comparison between catchments
368 with different characteristics, e.g., a different climatology, is performed or when
369 the relaxation of some of the assumptions is necessary. For the purposes of this
370 work the basic formulation is used.

371 The topographic index is computed from the slopes, with an algorithm that
372 calculates the path of the water based on the maximum slope at every point and

373 counts the contributing cells for every pixel. The higher values of topographic
374 index correspond with the river channels (cells that receive the largest contri-
375 bution from the catchment), while low values of TI are characteristics of cells
376 that receive small contributions in, e.g., headwater catchments.

377 **2.4.2 Depth-to-Water Index**

378 An alternative topographic index is represented by the Depth-to-Water (DTW)
379 index. It is a measure of the difference in elevation between each cell and the
380 closest river cell which it is most likely hydrologically connected to (*Murphy et al.*
381 (2009); *Rennó et al.* (2008) presents a different formulation, but an analogous
382 concept).

383 *Murphy et al.* (2009) start from the DEM-derived slope and a flow-channel
384 grid. An iterative function selects for every cell in the domain the nearest
385 surface water cell and calculates the path that connects the two cells. This is
386 then multiplied by the grid cell size, therefore approximating the total difference
387 in elevation between each cell and the corresponding river cell. In this way, to
388 each cell is assigned the value of

$$DTW = \left[\sum \frac{dz_i}{dx_i} a \right] x_c \quad (6)$$

389 where $\frac{dz}{dx}$ [-] is the local slope, i indicates the cell along the path, a is a coefficient
390 that takes into account the direction of the flow across the cell (it is 1 when the
391 flow is parallel to the grid lines and $\sqrt{2}$ when the flow is diagonal) and x_c [m]
392 is the cell size (*Murphy et al.*, 2011). The river network highly influences the
393 values and the pattern of the index. Generally, the hydrographic information
394 on the area are used to determine wheter a cell belongs to the river network or
395 not.

396 Low values of DTW indicate the tendency to have water at or near the

397 surface, while drier areas have higher values, indicating a longer distance from
398 the saturated areas (*Murphy et al.*, 2007). In the river channels, the *DTW* is zero
399 by definition. Since the value assigned to each cell is the difference in elevation
400 between that point and the associated river cell, the *DTW* index represents the
401 elevation normalized with respect to the river network and corresponds to the
402 relative position of the cell with respect to this datum.

403 The *DTW* index is also calculated from the slopes, with an algorithm that
404 follows the flow of water (downslope) from each cell to the nearest (in the least
405 cumulative slope sense) river cell. The value associated to each cell is the sum
406 of the slope along the path, multiplied by the size of the cell, which yields the
407 difference in elevation between them. In our implementation of the algorithm,
408 only flow directions parallel to the cell borders are allowed (*D4*); the coefficient
409 α is always 1. The cells are defined to be river cells according to a threshold
410 in contributing area, which is also calculated based on the slopes. In order to
411 ensure consistency, a comparison to the map of the rivers in the area and to
412 the values of the average water table depth obtained from the simulation was
413 performed. A threshold of 20 cells corresponding to 20 km² was found to be
414 satisfactory.

415 **3 Results and discussion**

416 **3.1 Exploratory analysis of data**

417 In this section, the analysis of the results of the above mentioned simulations is
418 presented, with a particular focus on the influence of soil composition and land
419 use on the energy fluxes, and on the relation of the different variables with the
420 topographic indices.

421 In the first part, the relationship between the latent heat flux and water

422 table depth is depicted. The two topographic indices, which will be used as
423 predictors in the statistical model, are then briefly discussed and analyzed. For
424 comparison, the relationship of latent heat flux with soil texture and land use
425 are presented. Finally, the difference in latent heat flux between the two sets
426 of simulations is analyzed, with respect to the predictors and other parameters,
427 such as the land use and soil composition. The analyses focus mostly on the
428 summer months and central hours of the day, since the difference in latent heat
429 due to soil moisture limitations is expected to be largest in these times, in the
430 study region (*Rahman et al.*, 2014).

431 **3.1.1 Relationship of the latent heat flux to the water table depth**

432 For the purpose of this analysis, the yearly average of water table depth is
433 considered, in order to emphasize the relation to static parameters, such as the
434 topographic indices.

435 Figure 4 shows the scatter plot of the monthly average latent heat flux (for
436 the month of July) versus the water table depth, coloured according to land use
437 (top) and soil texture (bottom). A typical pattern is present (see, e.g., *Szilagyi*
438 *et al.* (2013); *Kollet and Maxwell* (2008)), where cells with a deep water table
439 (over ~ 5 m) show lower latent heat and cells with very shallow (under ~ 1 m)
440 water table have the highest values in latent heat. In these two extremes, the
441 relation between latent heat and water table depth is weak, and small variations
442 in water table depth do not influence the latent heat flux. Conversely, between
443 these two extremes, the transition zone shows a steep relation between the two
444 variables. This means that a small difference in water table depth results in a
445 large variation in latent heat.

446 The month of July and the central hour of the day, 13.00, were chosen be-
447 cause of their larger values of latent heat. In the winter months (October to
448 March) there is no definition in the pattern and no S shape is visible. Dif-

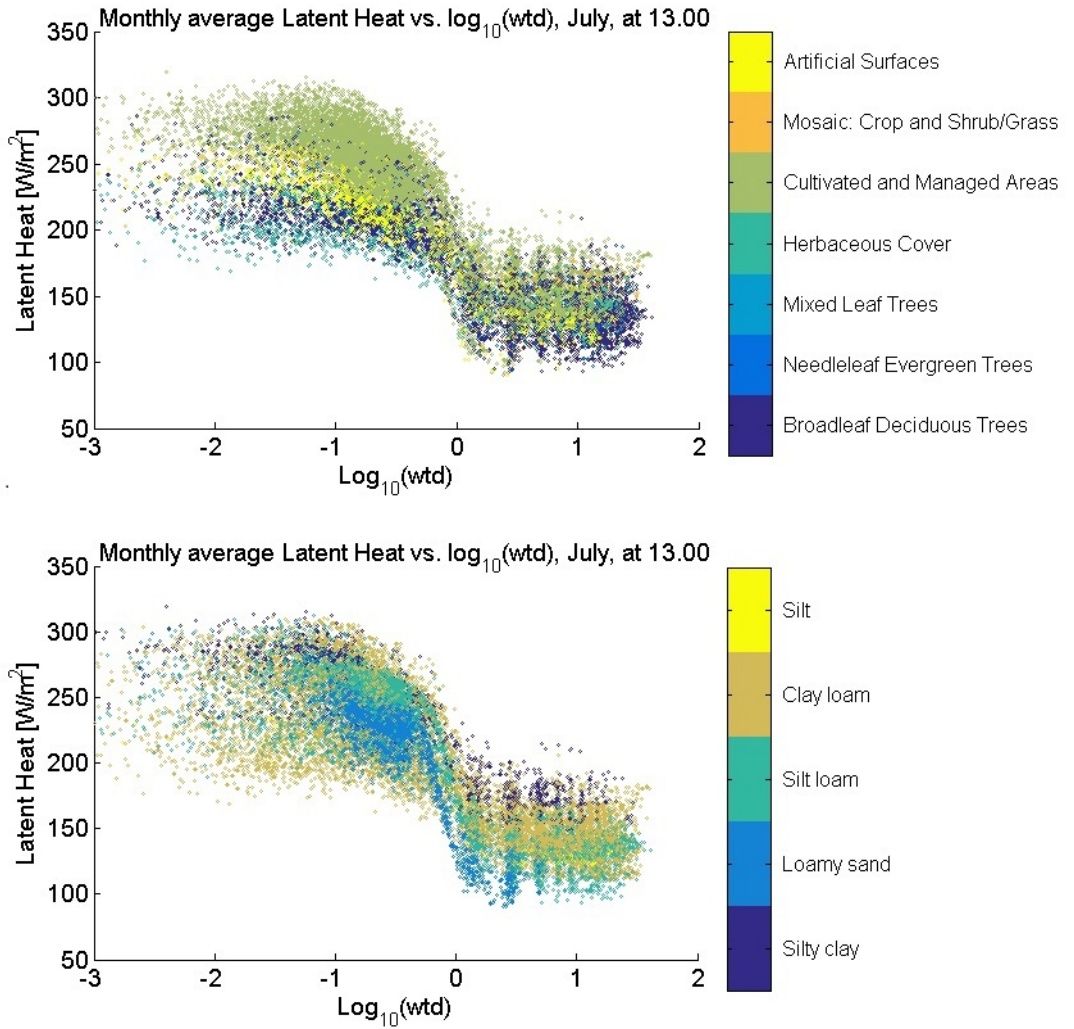


Figure 4. Scatter plot of the monthly average latent heat flux, for the month of July at 13.00, against logarithm of water table depth. The dots represent single cells in the domain and are coloured according to land use (top) and soil texture (bottom). Only cells with $wtd > 10^{-3}$ m are displayed.

449 ferent land uses and soil textures present different values of latent heat, e.g.,
450 the herbaceous cover does not reach the high values shown by vegetation with
451 higher leaf area index. With regard to the soil texture, the values of latent heat
452 for silty clay mostly exceed those found for silt loam and loamy sand. While all
453 these relations can be explained by the different hydraulic conductivities (for
454 the soils) or root depths and leaf area indices (for the vegetation), the position
455 of the cells in the domain also determines the availability of water, whose effect
456 is superposed on the physical characteristics of the land cover and soil texture.

457 **3.1.2 Analysis of the topographic indices**

458 The Topographic Index for the domain is shown in Figure 2. The river channels
459 correspond to the highest values of TI , but many other paths are visible, even
460 where the water is not ponded over the surface, that correspond to the directions
461 of the gravity driven water flow in the subsurface.

462 With respect to TI , which increases along the high flow accumulation ar-
463 eas represented by the river channels and, more generally, by converging areas,
464 forming narrow, discrete lines, the DTW index shows a smoother pattern (Fig-
465 ure 2). In particular, DTW increases slowly in the flat northern part of the
466 domain, while the increment is faster in the steeper terrain of the mountainous
467 southern region.

468 The analysis of $\log_{10}(DTW)$ is useful to have a clearer image of the flatter
469 area, where the index increase slowly with the distance from the river. For the
470 similar, although inverted dependence on the slope, the $\log_{10}(DTW)$ shows a
471 pattern similar to TI . In fact, there is a linear relationship between the two, as
472 shown in Figure 5. The values are averaged using a moving average over squared
473 neighbourhoods of $4*4$ cells, as in *Murphy et al. (2011)*, in order to remove
474 small-scale variability and get a clearer picture. The red line shows the linear
475 fit, which has a coefficient of determination of ~ 0.81 . The inverse relationship

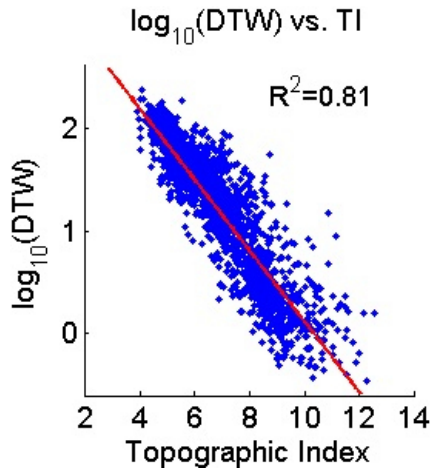


Figure 5. Scatterplot of $\log_{10}(DTW)$ and TI . The variables were previously averaged over 4 cells * 4 cells neighbourhood. The red line shows the linear fit, $\log_{10}(DTW) = -0.34 * TI + 3.57$.

476 between the two indices is due to their formulation: the topographic index
 477 accumulates the contributing area that is upslope with respect to the cell, while
 478 the DTW measures the distance (in height) between the cell and the closest river
 479 cell that is downslope. On the other hand, they both use the same algorithm
 480 for the determination of the path and both depend on the slope distribution of
 481 the catchment (but a logarithm is applied on the TI), which explains the close
 482 agreement between them.

483 3.1.3 Relationship between Latent Heat Flux and Topographic In- 484 dices

485 The topographic wetness index was developed to parameterize the water table
 486 depth, and therefore it is related to the soil moisture in the uppermost soil
 487 layers. Evapotranspiration is affected by the availability of water in the soil.
 488 The relation between water table depth and the land surface energy fluxes has
 489 been demonstrated in the past (*Kollet and Maxwell, 2008*) and also shown in
 490 Figure 4. For this reason we can expect to find a dependence of latent heat flux

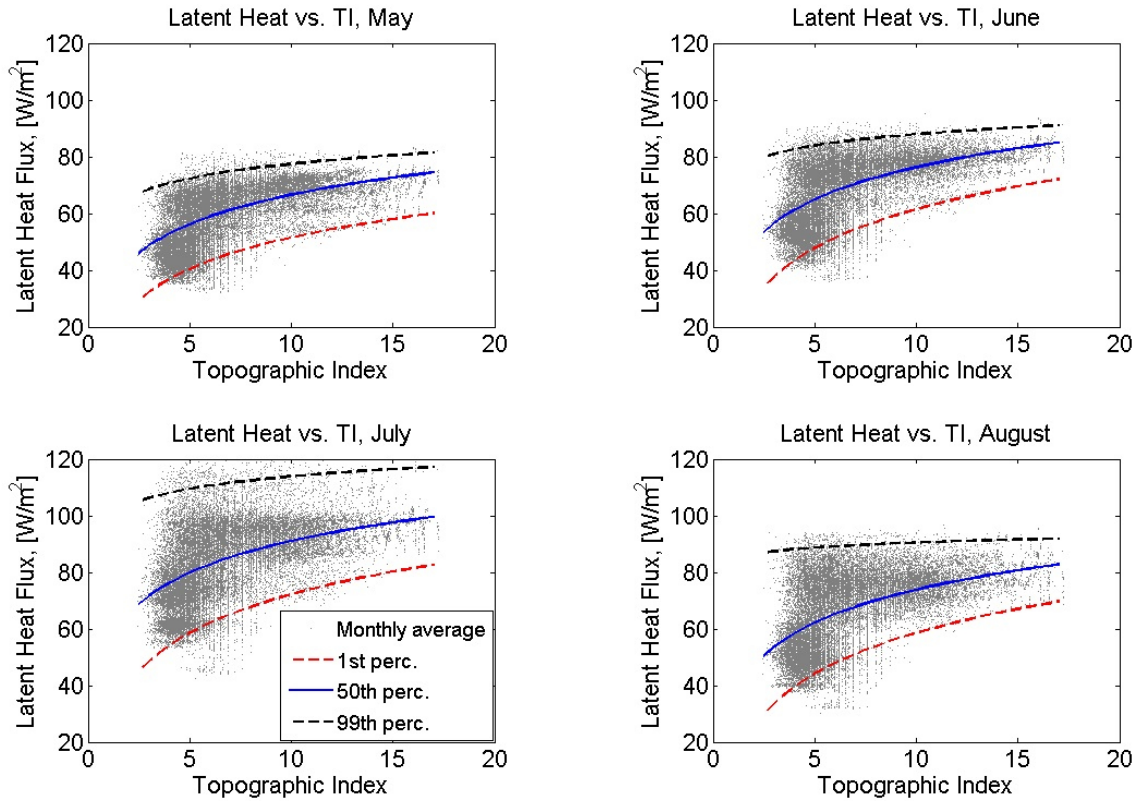


Figure 6. Scatter plot of the monthly average of latent heat against topographic index for the months from May to August. The lines represent the logarithmic fit of the 1st, 50th and 99th percentiles over small intervals of TI . Every cell in the domain is represented by its average value over the month.

491 on the topographic indices, as these are proxies for the water table depth.

492 Figure 6 show the scatter plots of the monthly average of latent heat flux
 493 and the topographic index, for every cell in the domain. Even if the values of
 494 latent heat flux show a large scatter for the same value of topographic index,
 495 a relationship can be found in the 1st, 50th and 99th percentiles, which were
 496 computed over TI bins of size 0.5.

497 While in winter (not shown here) the radiation is the limiting factor for
 498 the evapotranspiration, in summer this happens only for the cells that are not

499 limited in soil moisture. In the case of high topographic index ($TI > 12$), the
500 water table is shallow and there is full availability of water, that can fulfill the
501 atmospheric demand. The flat relationship between the latent heat and TI over
502 a certain threshold reflects the fact that the increment in soil moisture does not
503 automatically reflect into more evapotranspiration and is also consistent with
504 the relationship of latent heat to water table depth (see Figure 4). For low
505 values of topographic index, on the other hand, the water table is deeper, the
506 soil is not saturated and the system is water-limited.

507 Part of the scatter is due to the overlap of the effects of different kinds of
508 land use, as shown in Figure 7. Each colour corresponds to a different land
509 use class and every class is fitted using a first order Lowess technique, i.e. a
510 locally weighted regression method that reduces the influence of the outliers
511 by smoothing the curve and approximating the trend with local linear trends.
512 Every land use class presents similar trends, but for July the difference is much
513 larger than for the other months. For August, in particular, the water limitation
514 affected all the classes. It is also interesting to notice the different behaviour
515 of the herbaceous cover, which presents a lower latent heat flux, with respect
516 to the different categories of trees (broadleaved deciduous, needleleaf evergreen
517 and mixed leaf trees). Trees can produce higher evapotranspiration even in
518 areas with drier soil, corresponding to low values of topographic index. The
519 deeper root zone allows to reach deeper water tables and higher leaf area index
520 increases the transpiration.

521 The effect of the land use varies between months and is not always very
522 defined, because the resulting pattern is affected by other factors as well, for
523 example, the atmospheric forcings, such as radiation and precipitation, since
524 those vary within the domain.

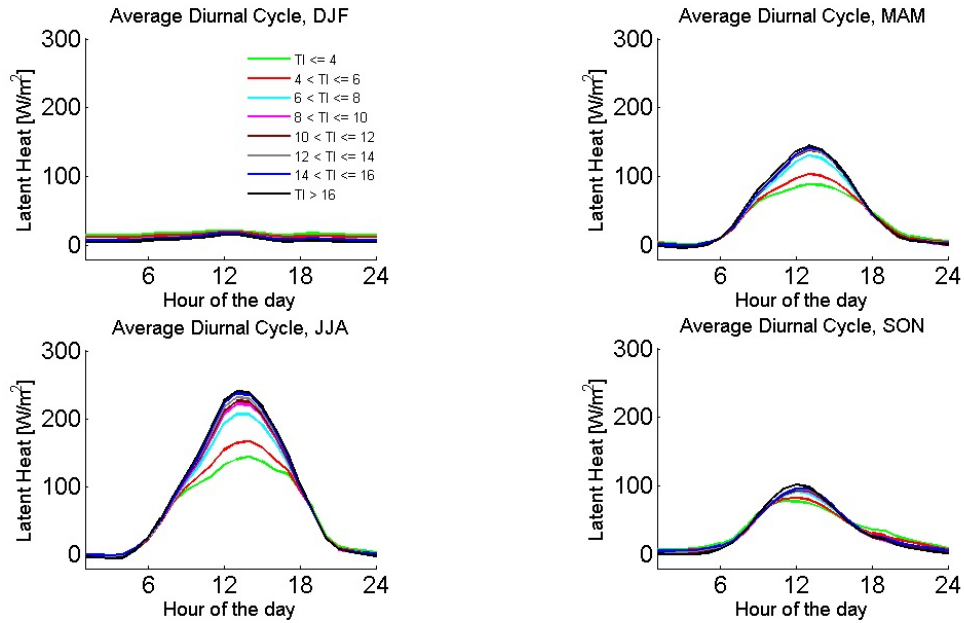


Figure 8. Overview of the seasonal average diurnal cycle of latent heat flux, for the different classes of TI .

525 3.1.4 Seasonal cycle of latent heat flux

526 Topographic index, as a measure of availability of water, is just one of the
 527 possible factors in determining the energy fluxes. Latent heat also has a diurnal
 528 and seasonal cycle, that reflects the availability of energy. Figure 8, shows
 529 the seasonal average diurnal cycle of latent heat flux for different classes of
 530 topographic index during the whole year. In order to obtain a smooth cycle
 531 and prevent spikes due to outliers, a 3-hour moving average was applied (see,
 532 e.g., *Deshpande and Goswami*, 2014).

533 The diurnal cycle shows higher values of latent heat for the summer months,
 534 in correspondence to the increased incoming radiation, as expected. Moreover,
 535 in these months the behaviour of the different classes of TI captures a larger
 536 variability, with maximum differences between the classes of TI of 50% around
 537 the middle of the day. This reflects the fact that neither energy nor water

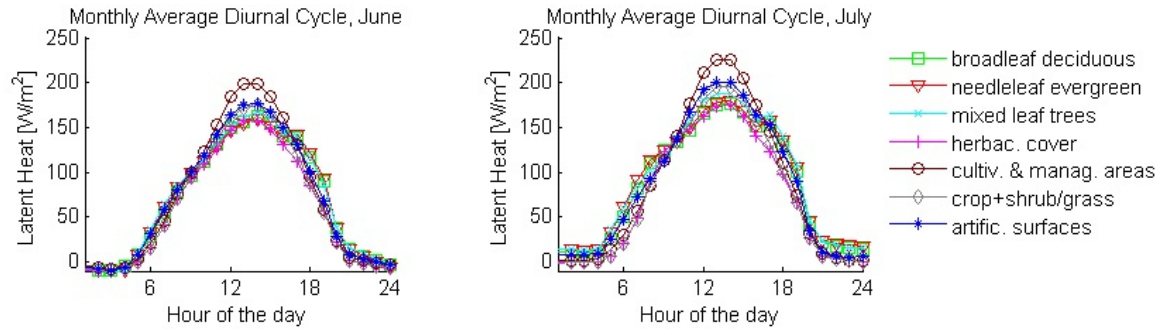


Figure 9. Monthly average diurnal cycle of latent heat flux for different classes of land use, for June and July. Every dot represents the average for one land use class and an hour of the day over the month.

538 are limited for cells with high TI in conditions of high incoming radiation,
 539 and is consistent with the larger dependence of LE on the groundwater during
 540 summer (*Rahman et al.*, 2014). During winter, on the other hand, the system
 541 is mostly energy-limited in this region of Germany and no real distinction is
 542 possible between the different classes of TI . For this reason we mostly focus on
 543 the summer months in our analysis.

544 It should be noted that the dependence on the topographic index does not
 545 only reflect a relationship to the hydrodynamics, since land use and soil are also
 546 partially correlated to topography (not shown) and are also key factors in LE .

547 3.1.5 Effect of land use and soil texture

548 As seen in Figures 6-7, the land use is also affecting the energy fluxes. It not
 549 only determines albedo, but is also central in the evapotranspiration processes.
 550 Figure 9 shows the diurnal cycle of latent heat for different kinds of land use,
 551 for two months. Land use is responsible for differences in the maximum (in the
 552 central hours of the day), but some variability is also present under conditions
 553 of very low incoming radiation, i.e. in the night hours, where the areas covered
 554 by trees show higher latent heat flux.

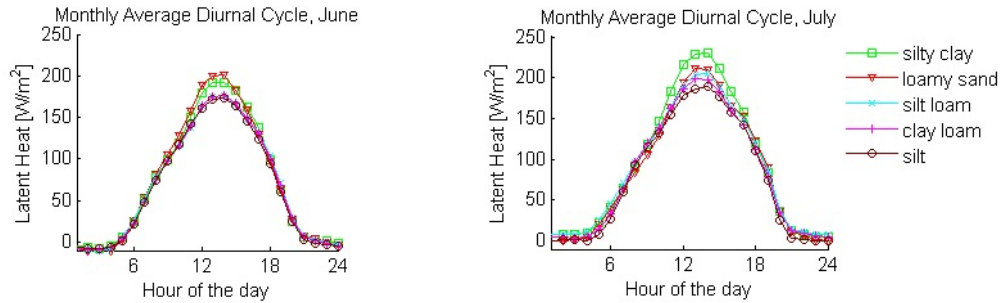


Figure 10. Monthly average diurnal cycle of latent heat flux for different classes of soil, June and July. Every dot represents the average for one soil type and an hour of the day over the month.

555 Figure 10 shows the monthly average diurnal cycle of latent heat flux filtered
 556 for the different soils for two months. The variability is less pronounced than
 557 for landuse, and is only present in the central hours of the day. Once again,
 558 it is important to notice that the effect of other variables, like landuse and
 559 topography, can be confounding factors.

560 3.1.6 Correlation of topographic index and latent heat flux

561 The main object of our analysis is the relationship between the topographic
 562 indices and the land surface processes and in particular the predictive skills of
 563 topographic indices with respect to the energy fluxes, also in comparison with
 564 other possible predictors (such as land use and soil texture). In the monthly
 565 average diurnal cycle (Figure 11), the topographic index TI shows a clear, direct
 566 correlation, i.e. higher values of topographic index correspond to higher values of
 567 LE flux for the central hours of the day and the difference between the maximum
 568 value for the highest and for the lowest class is larger than the difference between
 569 the classes of land use and between the classes of soil. The behaviour of the
 570 highest classes of topographic index do not show appreciable differences, since
 571 they are above the threshold in topographic index that corresponds to water
 572 tables at the surface, and so are virtually not water-limited.

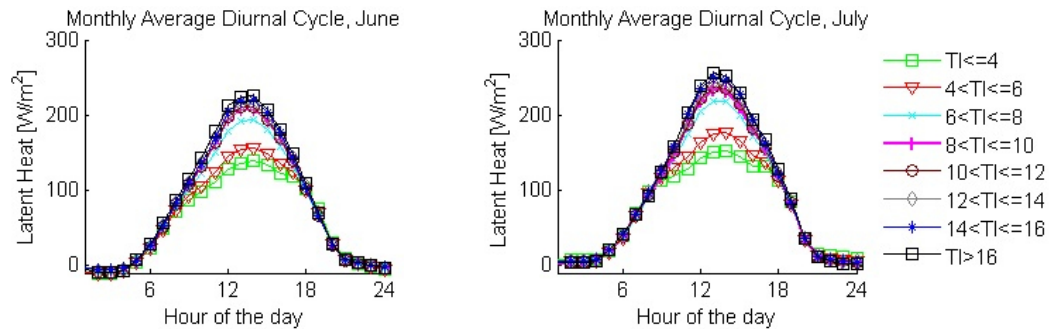


Figure 11. Monthly average diurnal cycle of latent heat flux for different classes of Topographic Index, June and July. Every dot represents the average for a class of TI and a hour of the day over the month. A 3 hour-moving average is applied.

573 This is in agreement with what was found previously in the scatter plots of
 574 the monthly average latent heat, but shows also a dependence on the hour of
 575 the day and a clear diurnal cycle for every class of TI , that was previously not
 576 visible. The monthly average diurnal cycles for classes of DTW (not shown)
 577 present an analogous pattern, with the classes corresponding to the highest
 578 availability of water having the highest LE .

579 3.1.7 Evapotranspiration surplus

580 In the case of the *PotLERun*, the water abundance in the cells does not depend
 581 on the TI , since the saturation is kept artificially at the surface. This means
 582 that useful information can be extracted from the comparison of the two runs,
 583 regarding the different behaviours of the cells in these two setups.

584 Figure 12 shows the map of the monthly average latent heat and potential
 585 latent heat, for July. While the potential latent heat mainly shows the signal of
 586 land use, with high values for the tree PFTs and lower values for the herbaceous
 587 cover, the latent heat in the *CplxRun* shows also the signal of topography (see
 588 Figure 2). For *PotLERun*, where the availability of water is kept artificially at
 589 its maximum, this signal is not present.

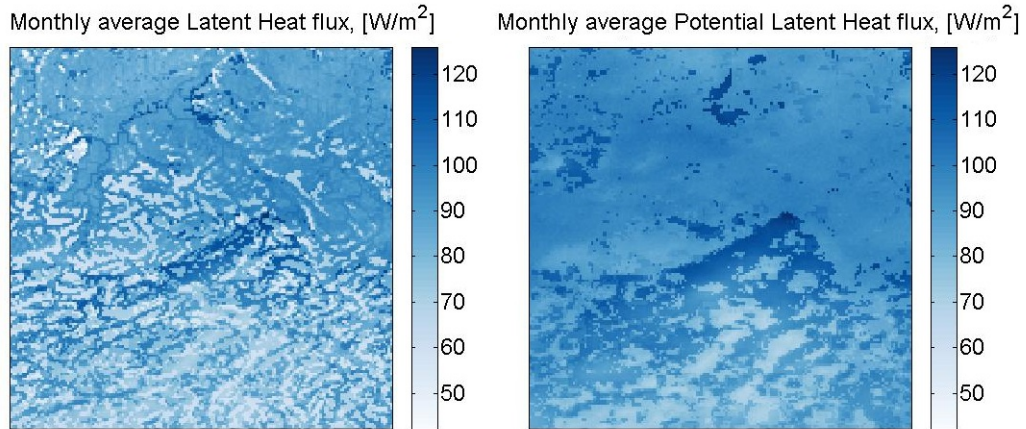


Figure 12. Map of the monthly average latent heat for the month of July, for the *CplxRun* (left) and for the *PotLERun* (right).

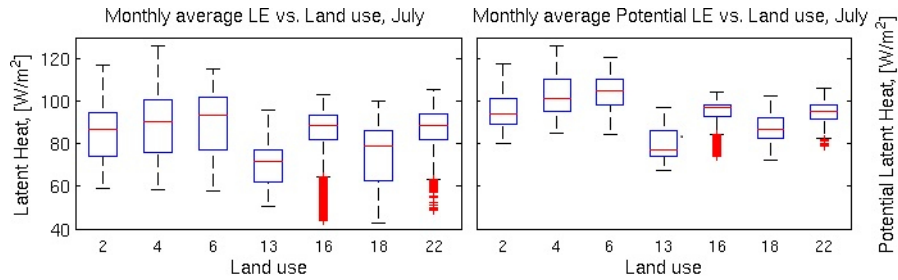


Figure 13. Box plots of the monthly average actual (left) and potential (right) latent heat flux (25th, 50th and 75th percentiles in the box, whiskers up to the most extreme non-outliers points and red crosses for the outliers) for different land uses, for the month of July. For the land use map, the correspondence is: 2) broadleaved deciduous trees; 4) needle-leaved evergreen trees; 6) mixed leaf type trees; 13) herbaceous cover; 16) cultivated and managed areas; 18) mosaic: cropland/shrub or grass cover; 22) artificial surfaces and associated areas.

590 Figure 13 shows the distributions of actual and potential latent heat flux
591 for the month of July, for the different land use and soil type. In case of the
592 potential latent heat, the first three boxes, that correspond to the tree cover,
593 present the highest values, but this is less clear in the case of the actual latent
594 heat, where the variability is larger because the availability of water also becomes
595 an important factor. Moreover, the distributions are distinctly larger and the
596 (ΔLE) values smaller for every land use in the actual latent heat, where the
597 moisture limitation lowers the evapotranspiration in most of the cells.

598 We define *evapotranspiration surplus* the difference between the potential
599 and the actual evapotranspiration in a cell, i.e. the evapotranspiration in the
600 case of *CplxRun* and *PotLERun*, respectively.

601 Figure 14 shows the map of average ΔLE for the month of July. The signal
602 of topographic index (Figure 2) is clearly visible. This is consistent with the
603 fact that the only difference between the two runs is in the availability of water,
604 which is strongly dependent on the topography in one case and kept constant in
605 the other. Negative values of ΔLE , i.e., cells which present a monthly average
606 potential latent heat lower than the actual latent heat, are rare but possible; the
607 higher rate of evapotranspiration causes a drop in temperature that influences
608 the evapotranspiration itself.

609 As already observed while analyzing the influence of TI on the latent heat,
610 the evapotranspiration is strongly dependent on the availability of water. This
611 is reflected in Figure 15, where the box plots of distributions of ΔLE for the
612 different classes of TI are depicted. At high values of TI correspond no limita-
613 tion in water and the evapotranspiration depends on the other parameters, first
614 of all the energy. At low values of TI , on the other hand, the difference is larger.
615 While the effect is clear for the median values, the spread of the distribution is
616 large, in particular for the most populated classes of TI . The same dependence

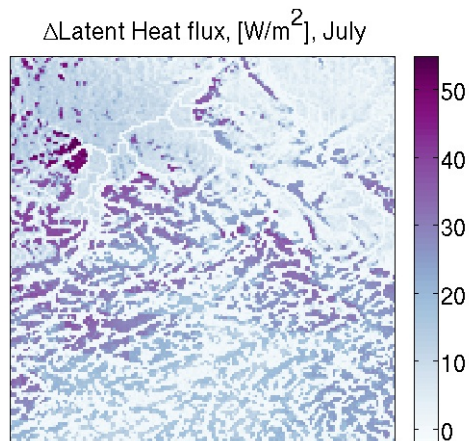


Figure 14. Map of the monthly average ΔLE for July, that clearly shows the signal of the topographic index.

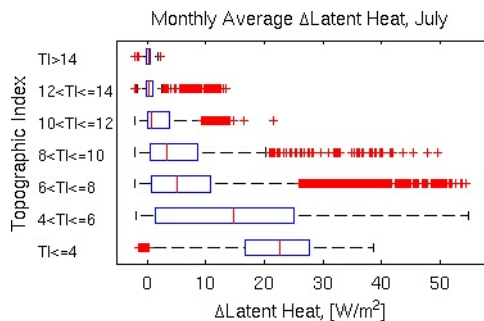


Figure 15. Box plots of the monthly average difference between potential and actual latent heat flux for different land uses, for the month of July.

617 of ΔLE on TI is present also in Figure 16, where the monthly average diurnal
 618 cycle of ΔLE for different classes of TI is shown. During the night, there is
 619 no visible difference between the TI classes. For the central hours of the day a
 620 clear dependence on the topographic index is visible. While for high values of
 621 TI the difference between the runs is close to zero, because the latent heat is at
 622 its potential, for low values of TI the difference becomes large, because in the
 623 *CplxRun* those cells are water-limited. The variability between the TI classes
 624 increases towards summer, with more classes exhibiting non-zero difference.

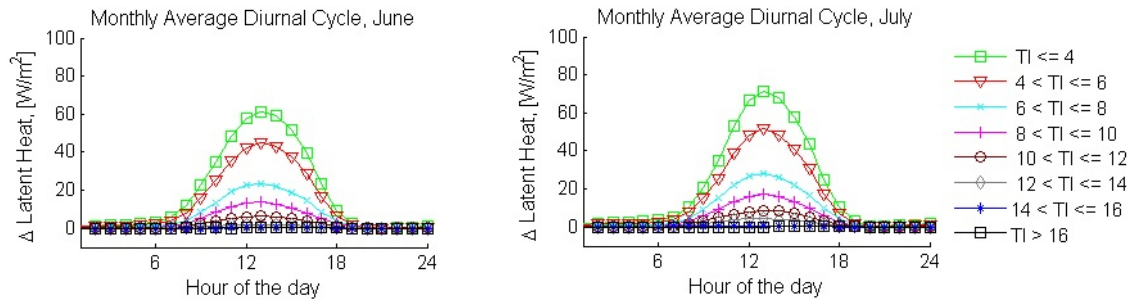


Figure 16. Monthly average diurnal cycle of ΔLE . The curves show the median value for each class of Topographic Wetness Index. A 3h-moving average is applied to the single hour values.

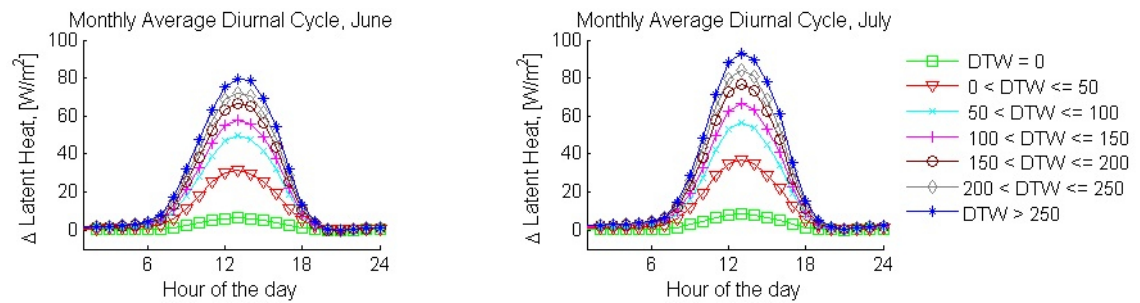


Figure 17. Monthly average diurnal cycle of ΔLE . The curves show the median value for each class of Depth-to-Water.

625 In Figure 17, the monthly average diurnal cycles for classes of DTW are
 626 depicted, for the months of June and July. As expected, and as already shown for
 627 TI , the increased availability of water in the classes with lower DTW is reflected
 628 in a smaller ΔLE . The difference is maximal when there is less limitation in the
 629 radiation (summer months, central hours of the day), while it is approximately
 630 zero during the night (or in the winter months, not shown here).

631 The shape of the diurnal cycle of ΔLE reflects the dependence on the in-
 632 coming radiation.

633 3.2 A model for latent heat flux

634

635 **3.2.1 Validation method**

636 In order to demonstrate the ability of the topographic indices to quantify the
637 ΔLE , the following procedure was applied. The entire domain was subdivided
638 into two subsets, one for the training and one for the validation of the method.
639 For the training data, the information coming from the *PotLERun* and the
640 characteristics of the cells (e.g., the topographic indices) were used as predictors
641 to develop a model for ΔLE . For validation, the outputs of the *CplxRun* were
642 used.

643 The two subsets are organized in a “checkers” scheme, where the dark squares
644 represent the training data and the whites are the validation, and vice versa.
645 To ensure independence, the size of the squares needs to be large enough, thus
646 the correlation length of the ΔLE was estimated. The analysis of the variogram
647 shows it to be no larger than 5 km, which means that squares of 21 km of side
648 length are a reasonable choice.

649 **3.2.2 Statistical model**

650 The diurnal cycle on one subset was fitted with a modified Gaussian function,

$$F(t) = A_0 + A * \exp\left[-\frac{(t - t_0)^2}{2 * w}\right] \quad (7)$$

651 using an offset A_0 , the difference between the maximum and minimum values
652 as height A , $t = 13$ as the central hour, t_0 , and a width, w , of 7 hours, for each
653 class of the topographic index. The parameters were estimated by means of a
654 dummy distribution with the same shape as the diurnal cycle over the month
655 of July (where the bell is more pronounced) and checked on the other months.

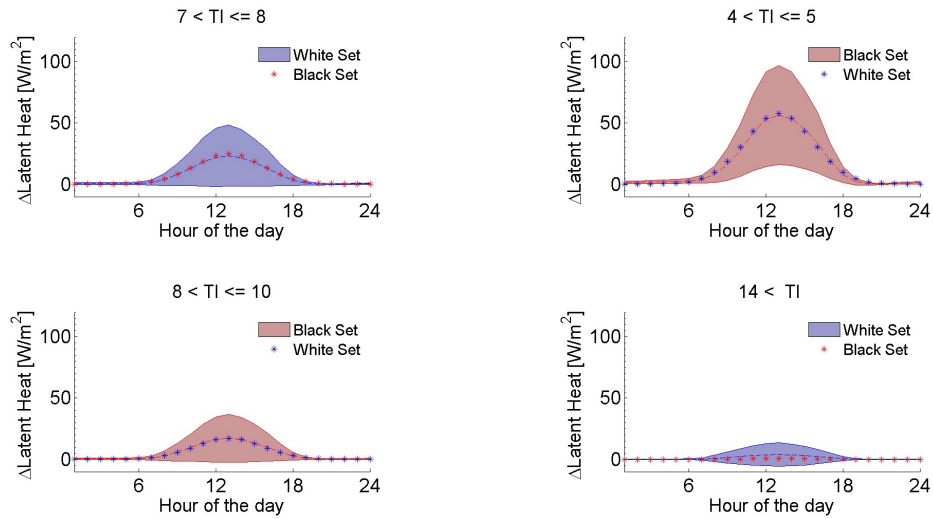


Figure 18. Examples of the comparison between the distribution of values of ΔLE for the black (white) subset of the domain -i.e. the validation subset- and the bell calculated on the white (black) subset for the same class of TI - i.e. the training subset. The dashed line represents the mean for the class and the filled area gives the standard deviation of the model. The stars show the values predicted for that hour and that class of TI , based on the corresponding data in the other subset.

656 3.2.3 Validation results

657 The plots in Figure 18 depict some examples of the monthly average diurnal
 658 cycles of ΔLE for a single class of TI . In order to represent the distribution
 659 of values, the mean (dashed line) and an interval of two standard deviations
 660 are displayed. The value predicted based on the information provided by the
 661 other subset are added for comparison (stars). In most of the cases, the function
 662 developed on one subset is able to reproduce the mean well in its counterpart,
 663 but some TI classes exhibit a large spread.

664 Similarly, in Figure 19 some examples of the monthly average diurnal cycles
 665 of ΔLE for single classes of DTW are depicted. As for the TI , also DTW is
 666 able to catch the average behaviour in each class fairly well, but the spread in

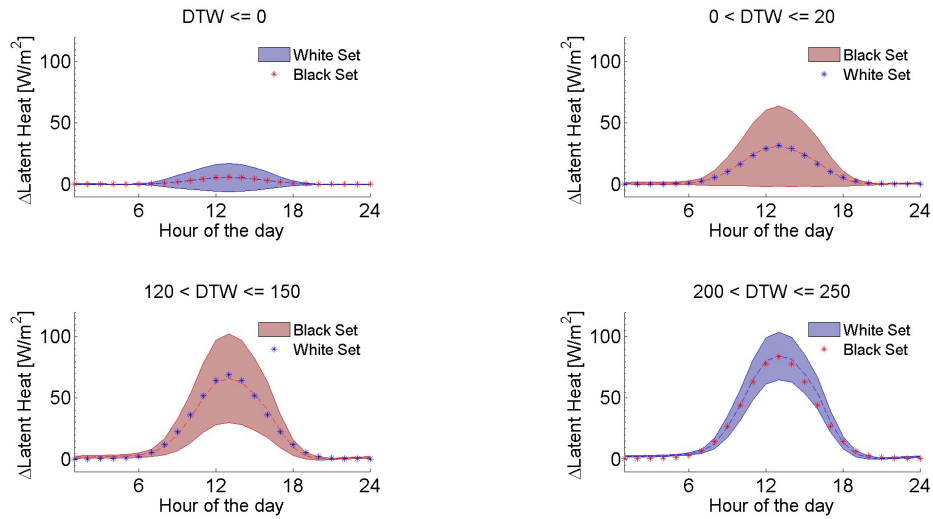


Figure 19. Examples of the comparison between the distribution of values of ΔLE for the validation subset and the bell calculated on the training subset. The dashed line represents the mean for the class and the filled area gives the standard deviation of the model. The stars show the values predicted for that hour and that class of DTW , based on the training subset.

667 the distributions is quite large.

668 When the value at the central hour is captured correctly, Equation 7 repre-
 669 sents fairly well the values during the rest of the day. The central hour is also
 670 the timestep were the spread in the classes is largest. Figure 20 shows the map
 671 of the difference between the values of monthly average ΔLE predicted by the
 672 model and those simulated in the *CplxRun*, in the central hour of the day, for
 673 the model based on *TI* (left) and *DTW* (right). While the mean over the do-
 674 main is close to zero in both cases, a clear pattern is present. Both negative and
 675 positive values are present (indicating, respectively, under- and overestimation
 676 of the latent heat flux), with mostly small scale structures in the southern part
 677 and a region with very high errors in both the models.

678 In order to study the origin of the larger scale structures in the bias, its
 679 relationship to the different landuses and soil composition was analyzed. In

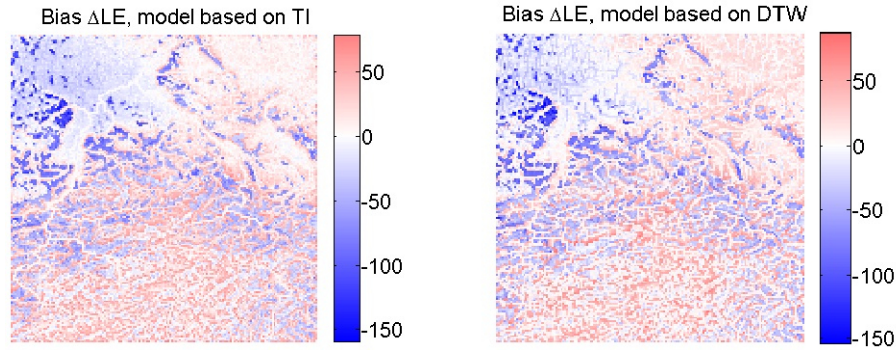


Figure 20. Maps of the difference between the monthly average values of ΔLE predicted and the values obtained from the simulation, for the central hour (13:00) of the day and the month of July. The prediction is based on TI and on DTW , respectively.

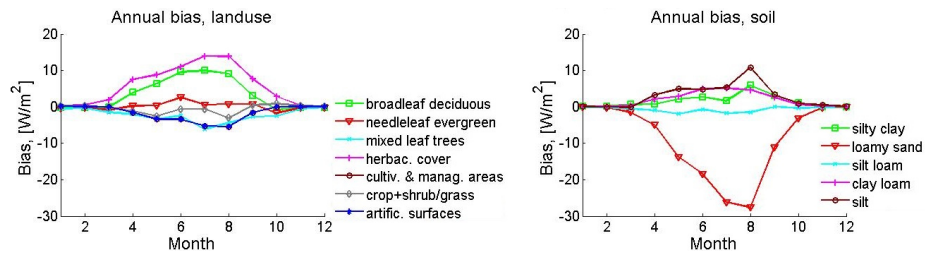


Figure 21. Plot of the mean bias of every class of landuse (left) and soil (right), for each month of the year at 13.00.

680 Figure21 , the annual trend of the prediction bias (based on TI) of the different
 681 classes is depicted, for both landuse and soil. While all the different landuses
 682 show comparable results, one of the soil types, loamy sand, presents a very high
 683 negative bias for the all summer months. This is in agreement with the large
 684 scale structure in the map of bias (Figure 20)

685 As an alternative form of validation, the results of the statistical model were
 686 tested against a free-drainage (FD) simulation (*Rahman et al.*, 2016). While
 687 this kind of land surface model is known to be a strong simplification, it still
 688 represents a widely used approach. The range of the error is equally large, yet
 689 the FD run shows a localized bias and poorly captures the spatial mean.

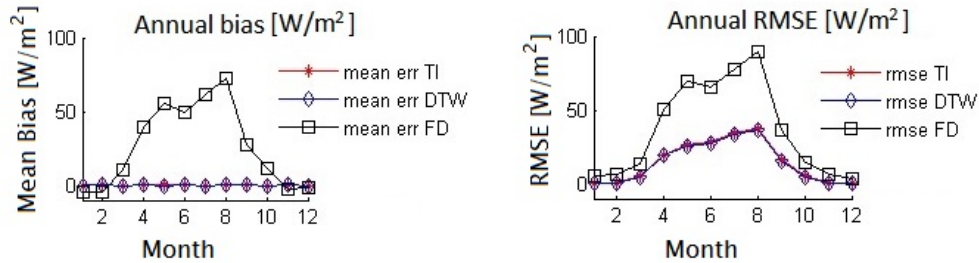


Figure 22. Comparison of the annual cycle of the root mean square error (left) and mean bias (right) for the free drainage simulation and the statistical models based on TI and DTW , at 13.00, for the monthly averages of LE .

690 The comparison of the root mean square error for the models (Figure 22)
 691 shows similar performances for the two statistical models, and a better perfor-
 692 mance compared to the free-drainage simulation. The choice of the central hour
 693 of the day is meant to serve as a worst case scenario, since that is the condition
 694 where the error is maximal. The fact that the bias is close to zero is a confir-
 695 mation of the assumption that the mean ΔLE for the classes is representative
 696 of the value for the single cells. This means that it is possible to predict the
 697 values for areas where only the simplified model was run, based on the class of
 698 topographic indices and the results of the full simulation in the training set, and
 699 to obtain an accurate spatial mean that can be provided as boundary condition
 700 to larger scale models.

701 4 Summary and conclusions

702 Groundwater is an important factor for the simulation of the energy fluxes at
 703 the land surface. Unfortunately, a full-physics representation of the subsurface
 704 hydrodynamics is mostly not feasible for climate simulations with long runs or
 705 large domains. We propose an approach that reduces the computational burden,
 706 by using a parameterized run and corrections based on the sensitivities of the

707 energy fluxes, and in particular of the latent heat flux, to topographic indices.

708 Two sets of simulations were used in the development of the model. The
709 first simulation, *CplxRun*, is a full-physics simulation, the results of which rep-
710 resent the true values of the variables. The second simulation, Potential Latent
711 Heat Run, *PotLERun*, is a highly parameterized version, where the water table
712 depth is artificially kept close to saturation. This serves the purpose of saving
713 computational time and shedding light on the behaviour of non water-limited
714 cells, since the influence of the water availability is subtracted.

715 From the analysis of the results of the *CplxRun*, it is visible how the latent
716 heat flux is strongly influenced by the availability of energy, as shown by the
717 dependence on the time of the year and hour of the day, and by the availability
718 of water. When the incoming radiation is not sufficient to trigger the evapo-
719 transpiration (in the winter months and in the night hours all over the seasons),
720 the latent heat flux is close to zero and no evapotranspiration is present even
721 for the *PotLERun*, despite the major water content in the soil. Even in the case
722 of full availability of water, this does not translate into a systematic increase in
723 evapotranspiration (Figure 6), since the energy is also a limiting factor.

724 Through the comparison of the latent heat in the *CplxRun* to its counter-
725 part under conditions of full saturation (*PotLERun*), we were able to isolate the
726 effect of the topographic indices and develop a statistical model to calculate the
727 actual LE from the results of a parameterized run. The two topographic in-
728 dices, the Topographic Index, TI , and Depth-To-Water, DTW , because of their
729 relationship to the water table depth, are good proxies for the water availability,
730 and show in general a significant effect on the diurnal cycle of latent heat flux,
731 with respect to the land use and soil texture. The average diurnal cycles for the
732 different classes of TI present a constant pattern over the year (Figure 8), where
733 the high values of TI are related to the higher values of latent heat flux. While

734 the relationship between latent heat flux and topographic indices exhibits too
735 much scatter to be able to establish a simple mathematical relationship with
736 sufficient confidence, it was possible to develop a statistical model for the de-
737 termination of the maximal value of the difference in evapotranspiration, ΔLE ,
738 corresponding to the central hour of the day, for each class of the predictor (TI
739 or DTW). This value was then used to fit the top of the bell that represented
740 the diurnal cycle.

741 The difference in latent heat between the two runs, evapotranspiration sur-
742 plus (ΔLE) shows a marked relationship to the topographic indices (Figure 16),
743 since everything is kept constant between the two simulations, except for the
744 position of the water table. This means that the availability of water and all
745 the quantities that derive from it, are well represented in the difference. The
746 diurnal cycle of ΔLE for the classes of TI and DTW shows a bell shape, with
747 the highest classes of TI and lowest classes of DTW presenting the lowest values
748 of ΔLE (since they approximate their full potential in moisture).

749 The diurnal cycle for every class was then fitted with a modified Gaussian
750 bell, that reproduces fairly well the diurnal cycle of ΔLE . While the mean values
751 for each class are well behaved and are ordered according to the topographic
752 index, the spread in some of the classes is very large. This is due to the fact
753 that topography is not the only parameter influencing the surface energy fluxes.
754 While part of the information about landuse and soil, for example, is present in
755 the topographic indices, for the natural relationship between topography and
756 surface characteristics, part of it is lost.

757 The validation of the method, through the extraction of two subsets and the
758 comparison of the results obtained on the training subset to the distributions
759 of value on the validation subset, showed a good agreement in the values of the
760 mean. The domain was subdivided into two subdomains. Under the assumption

761 that the topographic indices are good predictors for the ΔLE , the bell fitted on
762 the mean for each class of topographic index in one subset was superimposed
763 to the distribution of the same classes on the second subset. The possibility of
764 dividing the domain into two regions (east-west or north-south) was explored
765 and had to be discarded. The major objection against the north-south sub-
766 division was due to the deeply different average elevation, the southern area
767 being mostly over 400 m.a.s.l. and the northern region being mostly flat and
768 around 200 m.a.s.l., and the related different precipitation rate. For the east-
769 west subdivision, the major concern was due to the different soil texture, and
770 in particular with the loamy sand being only present on one side of the domain.
771 The subdivision into two checkerboard subsets was able to capture the general trend
772 and to avoid discrepancies due to large scale trends, but showed mixed results.
773 While the model developed in the training subset was able to reproduce the
774 mean in the validation subset very well, for some of the classes the spread was
775 very large and this translated into large errors in the prediction of the ΔLE .

776 The two predictors, TI and DTW , do not show appreciable difference in the
777 root mean square error and bias, but exhibit some differences in the spatial
778 distribution. This is in agreement with the common basis of the two indices on
779 the slopes. When compared against the free drainage run, results of a simulation
780 where the soil moisture is allowed to leave the domain via gravity drainage,
781 the statistical model performs satisfactorily, both in the winter and summer
782 months. The low mean bias of the statistical model, in particular, indicates
783 that the spatial mean of the predicted latent heat flux is a good approximation
784 of the results provided by the full-physics model. In particular, the spatial mean
785 could be provided to $GCMs$ or $RCMs$ as the lower boundary flux and would
786 represent an improvement with respect to the free-drainage run.

787 Future work will substitute the discrete classes with continuous functions,

788 which will allow to reproduce the differences that are now neglected inside the
789 classes and, in particular, the steep increment of latent heat flux for low values
790 of topographic index TI . Further improvement may be achieved with an opti-
791 mization of the fit of the diurnal cycle (e.g., via a machine learning approach for
792 the estimation of the parameters over the different months). In an application,
793 the *CplxRun* would only be used to model small catchments in a part of the full
794 modelling area. Finally, an implementation of the concept over time should be
795 explored, with a statistical model based also on the atmospheric forcing. This
796 would allow to overcome the difficulties posed to the generalization of the results
797 by the heterogeneity in soil and landuse.

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