



1 **Implementation of global soil databases in NOAH-MP model and the effects on**
2 **simulated mean and extreme soil hydrothermal changes**

3 Kazeem A. Ishola^{1,3} Gerald Mills², Ankur P. Sati², Benjamin Obe², Matthias Demuzere⁵,
4 Deepak Upreti^{1,3}, Gourav Misra³, Paul Lewis³, Daire Walsh³, Tim McCarthy³, Rowan
5 Fealy^{4,*}

6 ¹Irish Climate Analysis and Research UnitS (ICARUS), Maynooth University, Maynooth, Ireland

7 ²School of Geography, University College Dublin, Dublin, Ireland

8 ³National Centre for Geocomputation, Maynooth University, Maynooth, Ireland

9 ⁴Department of Geography, Maynooth University, Maynooth, Ireland.

10 ⁵B-Kode VOF, Ghent, Belgium

11 *Correspondence to:* Kazeem Ishola (Kazeem.Ishola@mu.ie) and Rowan Fealy (Rowan.Fealy@mu.ie)

12

13 **Abstract**

14 Soil properties and their associated hydro-physical parameters represent a significant
15 source of uncertainty in Land Surface Models (LSMs) with consequent effects on
16 simulated sub-surface thermal and moisture characteristics, surface energy
17 exchanges and turbulent fluxes. These effects can result in large model differences
18 particularly during extreme events. Typical of many model based approaches, spatial
19 soil information such as location, extent and depth of textural classes are derived from
20 coarse scale soil information and employed largely due to their ready availability rather
21 than suitability. However, the use of a particular spatial soil dataset has important
22 consequences for many of the processes simulated within a LSM. This study
23 investigates NOAH-MP model uncertainty in simulating soil moisture (expressed as a
24 ratio of water to soil volume, $\text{m}^3 \text{m}^{-3}$) and soil temperature changes associated with two
25 widely used global soil databases (STATSGO and SOILGRIDS) across the Island of
26 Ireland. Both soil datasets produced a significant dry bias in loam soils, up to 0.15 m^3
27 m^{-3} in a wet period and $0.10 \text{ m}^3 \text{m}^{-3}$ in a dry period. The spatial disparities between
28 STATSGO and SOILGRIDS also influenced the regional soil hydrothermal changes
29 and extremes. SOILGRIDS was found to intensify drought characteristics - shifting
30 low/moderate drought areas into extreme/exceptional during dry periods - relative to
31 STATSGO. Our results demonstrate that the coarse STATSGO performs as good as
32 the fine-scale SOILGRIDS soil database. However, the results underscore the need to
33 develop detailed regionally-derived soil texture characteristics, and for better
34 representations of soil physics in LSMs to improve operational modeling and
35 forecasting of hydrological processes and extremes.

36

37 **Keywords:** soil moisture; soil temperature, droughts; Land surface model; soil
38 hydrophysical properties



1

2 1. Introduction

3 The pedosphere (or soil) is an important component of the Earth system and plays a
4 critical role in energy, water and biogeochemical exchanges that occur at the land-
5 atmosphere interface (Dai et al., 2019a,b). The accurate description and
6 representation of soil textural categories and/or soil hydro-physical properties is
7 fundamental to developing and enhancing Earth system modeling (ESM) capacity in
8 predicting land surface exchanges at different scales (Luo et al., 2016; Dai et al.,
9 2019a,b). This information is incorporated via the respective land surface model (LSM)
10 – the only physical boundary in an ESM and is a key component of any ESM framework
11 (Fisher and Koven, 2020; Blyth et al., 2021). However, accurate descriptions of soil
12 properties in LSMs are difficult to obtain due to the limited availability of high resolution
13 global-scale soil texture measurements or lack of regionally specific measured soil
14 properties (e.g. Kishné et al. 2017; Dennis and Berbery, 2021; 2022). This represents
15 a key limitation and is a source of model uncertainty in current LSMs (Li et al., 2018),
16 and consequently weather and climate models.

17 In many LSMs, soil hydrothermal properties such as saturated soil hydraulic
18 conductivity and diffusivity, porosity, field capacity, wilting point, saturated soil matric
19 potential, etc. are linked to soil textural classes/compositions in two ways. Typically,
20 models employ a model-prescribed look-up table, with values that are empirically
21 derived from existing/available in-situ soil surveys, to associate mean soil properties
22 with each soil type. The soil categories are identified by grouping soil samples with
23 similar properties using particle size analysis (e.g. Gee and Bauder, 2018). While this
24 option is computational efficient, it assumes that the derived values are globally
25 transferable which may not be realistic as soil properties vary both horizontally and
26 vertically. This approach is also dependent on having access to soil texture maps; the
27 scale and extent of which varies between different soil databases (Dai et al., 2019a,b;
28 Dennis and Berbery, 2022). In spite of this, the use of readily available global soil
29 texture maps in combination with model look-up tables is a standard practice in ESM
30 research. As an alternative approach, new state-of-the-art global soil information
31 datasets are being explored to constrain and improve the representation of soil
32 processes within LSMs (e.g. de Lannoy et al., 2014; Shangguan et al., 2014; Hengl et
33 al., 2017; Looy et al., 2017; Dennis and Berbery, 2021;2022; Xu et al., 2023). For some
34 LSMs, soil hydrothermal properties can be estimated from a set of equations known
35 as PedoTransfer Functions (PTFs) that require information on soil composition such
36 as sand, silt and clay composition and organic matter (Looy et al., 2017; Dai et al.,
37 2019a,b).



1 The existing PTFs are based on different approaches (Looy et al., 2017) including,
2 physically-based relationships or advanced statistical approaches based on machine
3 learning, random forest and neural networks (Lehmann et al., 2018; Zhang et al., 2018;
4 Or and Lehmann, 2019; Szabó et al. 2019). Clearly, the existing PTFs vary in
5 complexity. Thus, the choice of PTFs partly depends on the availability of inputs
6 (Weihermüller et al. 2021) and has been reported to impact soil moisture simulations,
7 with consequent effects on the surface energy and water fluxes, land-atmosphere
8 coupling, atmospheric moisture budget, boundary layer evolution and regional climate
9 (Dennis and Berbery, 2021; 2022; Weihermüller et al. 2021; Xu et al., 2023; Zhang et
10 al., 2023). Moreover, as soil moisture affects land-atmosphere interactions largely
11 through its control on the evaporative fraction (e.g. Seneviratne et al., 2010; Ishola et
12 al., 2022), soil hydrophysical properties play an important role in simulating climate
13 extremes (e.g. droughts) (He et al., 2023; Zhang et al., 2023). Weihermüller et al.
14 (2021), using the HYDRUS-1D model, reported that soil hydraulic properties estimated
15 from different PTFs resulted in substantial variability in the predicted water fluxes. In
16 this context, Dennis and Berbery (2021) and Dennis and Berbery (2022) employed soil
17 properties derived from two different sources, the STATSGO and the Global Soil
18 Dataset for Earth System Modelling (GSDE), in the Weather and Research
19 Forecasting (WRF) and Community Land Model (CLM) models, and found soil texture-
20 related differences in the surface fluxes that can lead to differences in the evolution of
21 boundary layer thermodynamic structure and precipitation development. This finding
22 is further supported by Zhang et al. (2023). Recently, Xu et al. (2023) demonstrated
23 that using state-of-the-art soil information, such as POLARIS and the 250 m SoilGrids,
24 can improve the performance of LSMs.

25 Here we focus on the response of the NOAH-MP LSM to soil information with the
26 objectives evaluating the model representation of land surface fields; however, a LSM
27 will also respond to changes in other drivers, such as vegetation (e.g. albedo, surface
28 roughness length, etc.) and meteorological forcing (Arsenault et al., 2018; Hosseini et
29 al., 2022). The first effort to implement SoilGrids in NOAH-MP LSM was recently
30 evaluated over Southern Africa (Zhang et al., 2023). Our study complements the
31 previous effort by evaluating the impact of combining the SoilGrids soil compositions
32 with PTFs. Specifically, we focus on the impact of two different soil datasets on
33 simulations of soil moisture and temperature during a period of normal and dry weather
34 conditions.

35

36 **2. Data and Methods**

37 **2.1 Background context of Ireland**



1 The Ireland is situated in a maritime temperate region where the climate is
2 predominantly influenced by the mid-latitude westerly warm airflow off the North
3 Atlantic Ocean, and occasional incursions of cold air masses during winter (Peel et al.,
4 2007). The long-term (1981-2010) average daily maximum temperature of the region
5 is between 18° and 20°C in summer and 8 °C in winter. Occasionally, the daily
6 minimum temperature drops below 0 °C in winter. Rainfall is distributed throughout the
7 year with mean annual value of 1200 mm. The west of Ireland typically experiences
8 higher rainfall amounts (1000-1400 mm), and may exceed 2000 mm in the upland
9 areas. Conversely, the east experiences lower rainfall amounts, between 750 and
10 1000 mm. More details on the background climate of Ireland are provided in Walsh
11 (2012). In relation to the general soil information (Figure 1a), the south-east is
12 characterized mainly by free draining sandy soils, peat soils dominate the mountains,
13 hills and western edge of the country, while limestone-rich soils dominate the midlands
14 and south (Creamer et al., 2014). Among the land cover types (Figure 1b), grassland
15 dominates the agricultural and total land area in Ireland. The temperate climate in
16 combination with fertile soils, mostly in the south and east where the soils are free
17 draining, provides conditions that are favourable to near year round grass growth.
18 However, the heavy clay (wet) soils limit grass growth in the west and north of the
19 country (Keane and Collins, 2004).

20

21 2.2 Model description

22 Here, we employ the advanced community NOAH-MP land surface model with multi-
23 parameterization options, with improved representation of physical processes (Chen
24 et al., 1996; Niu et al., 2011). The model is available as an uncoupled model, with the
25 capacity to simulate different land state variables (e.g. soil moisture) and land energy,
26 water and carbon fluxes. It also represents a LSM that is coupled with atmospheric
27 models such as the Weather Research and Forecasting (WRF) model (Barlage et al.,
28 2015). Due to its simplicity in selecting and combining multi-physics options, the model
29 has been widely used for different applications, including natural hazards, drought and
30 wildfire monitoring, land-atmosphere interactions, sensitivity and uncertainty
31 quantification, biogeochemical processes, water dynamics, dynamic crop growth
32 modeling, and soil hydrothermal processes. (Zhuo et al., 2019; Kumar et al., 2020;
33 Chang et al., 2022; Hosseini et al., 2022; Nie et al., 2022; Warrach-Sagi et al., 2022;
34 Hu et al., 2023).

35

36 In NOAH-MP LSM, the major improvements in mechanisms relevant to soil processes
37 are (1) distinguishing less and more permeable frozen soil fractions, (2) introducing an



1 alternative lower boundary soil temperature that is based on zero heat flux from the
2 deep soil bottom, (3) adding TOPMODEL and SIMGM models for runoff and
3 groundwater physics options (Niu et al., 2007), and (4) adding an unconfined aquifer
4 beneath the 2 m bottom of the soil layer to account for water transport between the soil
5 and aquifer. Relative to other LSMs, the NOAH-MP model framework is typical in its
6 ability to define soil properties either by using dominant soil texture linked to
7 empirically-derived soil parameter values, using soil texture with varying depths, or
8 using soil texture compositions derived using PTFs (Saxton and Rawls, 2006).
9 The prognostic equations from Mahrt and Pan (1984) are used to describe soil
10 moisture and soil temperature in the model (Chen et al., 1996).

$$11 \quad C(\theta) \frac{\partial T}{\partial t} = \frac{\partial}{\partial z} \left(K_t(\theta) \frac{\partial T}{\partial z} \right) \quad (1),$$

$$12 \quad \frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z} \left(D \frac{\partial \theta}{\partial z} \right) + \frac{\partial K}{\partial z} + F_\theta \quad (2),$$

13 where C is the volumetric heat capacity, θ is the soil moisture, T is the soil temperature,
14 and K and K_t are the hydraulic and thermal conductivities, respectively. D is the soil
15 diffusivity and F_θ are the sinks and sources of soil water, that is, evaporation and
16 precipitation.

17

18 2.3 Gridded data

19 Meteorological variables which are required as initial and forcing conditions are
20 obtained from the European Centre for Medium-Range Weather Forecasting (ECMWF)
21 database. We employ the state-of-the-art ECMWF ERA5-Land global reanalysis
22 product that provides data at 0.1° (~ 9 km) spatial and hourly temporal resolution
23 (Muñoz-Sabater, 2021). The required forcing variables include total precipitation,
24 incident shortwave and longwave radiation, 2m air temperature, 10m zonal and
25 meridional wind components, surface pressure and specific humidity. For initialisation,
26 the model also requires input fields of soil temperature, surface skin temperature,
27 canopy water and snow water equivalent at the first timestep. The hourly data for all
28 variables was obtained for the period 2009-2022.

29 NOAH-MP model also requires static geographical data (e.g. soil texture and land use)
30 and time varying vegetation products (e.g., leaf area index and fraction of green
31 vegetation). We use the STATSGO gridded soil categories map provided at 5 arcmin
32 resolution (~ 9 km) (FAO 2003a;b) and the International Soil Reference and Information
33 Centre (ISRIC) global SoilGrids data (Hengl et al., 2017; Poggio et al., 2021). The latter
34 is available at 250 m resolution and six standard soil depths, however, sand and clay
35 proportions are currently available at four layers and provided as part of the WRF



1 geographical data fields. Preprocessing of the data was undertaken in the WRF
2 Preprocessing System (WPS) (Skamarock et al., 2019).

3

4 2.4 Model simulations

5 We set up and ran an offline NOAH-MP model version 4.3 within the framework of the
6 High Resolution Land Data Assimilation System (HRLDAS) (Chen et al., 2007). Using
7 the WPS system, the model domain is set up as a 1 km grid space covering the island
8 of Ireland and the west coast of the United Kingdom (Figure 1). We incorporate a high
9 resolution land use dataset based on the 100 m raster CORINE Land Cover for 2018
10 (CLC 2018). The 44 CORINE land cover classes are initially reclassified into 21
11 categories to match the default modified IGBP MODIS 20-category land use (Figure 1
12 b). The data is then resampled to 250 m. To generate the required geographic files for
13 input to NOAH-MP, the CLC 2018 is converted to binary format which is used as input
14 to the WPS, which subsequently generates the gridded geographic information
15 required to run the NOAH-MP model. Other geographical data, such as topography,
16 green vegetation fraction and surface albedo used in this study are derived from the
17 model default datasets provided by the Research Application Laboratory, National
18 Center for Atmospheric Research (RAL/NCAR).

19 To investigate the effect of soil hydrophysical properties on model simulations of soil
20 moisture and soil temperature, we configure two experiments that are based on
21 different soil data options, namely, (1) dominant soil texture categories used as default
22 in WRF/NOAH-MP; and, (2) soil textural compositions in combination with PTFs
23 (Saxton and Rawls, 2006). The dominant soil texture option uses the baseline
24 FAO/STATSGO dataset with the empirically-derived soil properties from a look-up
25 table, while the PTFs-derived soil properties use the fine-scale SoilGrids sand and clay
26 proportions. The dominant topsoils across the domain are broadly classified into four
27 and two broad categories based on STATSGO and SoilGrids, respectively (Figure 2).
28 While Loam and Sandy Loam soil textures cover the largest area in both data sources
29 (Table 2), the extent to which the difference in the data and soil physics options
30 contribute to model uncertainty in NOAH-MP model is evaluated. Other NOAH-MP
31 physics options used are outlined in Table 3.

32 For the numerical experiments, the soil layer thicknesses of 0.07, 0.21, 0.72 and 1.55
33 m are used, with a cumulative soil depth of 2.55 m. The thicknesses are selected to
34 match the layers of initial soil input fields from ERA5-Land. The model is spun-up over
35 10 years for each experiment using the climatology of the hourly ERA5-Land for the
36 period 2009-2022, to bring the soils to thermal and hydrologic equilibrium with the
37 atmosphere. After spin-up, the model is assumed to be stable and is then used as the



1 point to initialise the simulations, reported on here, using the hourly meteorological
2 forcing from 2009 to 2022.

3

4 2.5 Station data

5 Profile measurements of soil temperature and volumetric water content are obtained
6 from two established eddy covariance grass flux sites, namely, Johnstown Castle and
7 Dripsey (Kiely et al., 2018; Murphy et al., 2022), and five new sites (as part of the
8 Terrain-AI project) at Athenry, Ballyhaise, Claremorris, Dunsany and Valentia. Terrain-
9 AI is an on-going large-scale project, which in part focuses on establishing a long-term
10 network of soil moisture monitoring sites across Ireland. It monitors and measures in
11 situ soil moisture contents using Time Domain Reflectometry (TDR) sensors installed
12 at different soil depths. Given that the Terrain-AI sites are new, the VWC
13 measurements are so far limited to a year, and are prone to outliers because the TDR
14 probes may require some time for the soil to settle and provide reliable measurements.
15 In addition, the soil temperature measurements obtained from Met Eireann for the
16 Terrain-AI sites are not homogenised or quality controlled. Despite the limitations of
17 the observed data from the Terrain-AI sites, they are the only station observations
18 available to evaluate our model results.

19 All the selected sites are distinguished by soil texture (Table 1) and contrasting soil
20 water regimes (Figure 1 a). For example, Johnstown Castle site is characterized by
21 seasonally dry and free draining sandy loam soils, whereas Dripsey is dominated by
22 heavy soils that retains water throughout the year (e.g. Ishola et al., 2020). Half-hourly
23 or hourly measurements are obtained for 2009-2012 period from Dripsey, 2018 (only
24 second half of the year), 2019 and 2021 from Johnstown Castle, and the year 2022 for
25 the Terrain-AI sites. Metadata for each station, outlining soil type, land cover and
26 altitude are provided in Table 1.

27

28 2.6 Satellite products

29 Global satellite soil moisture datasets (e.g. ESA-CCI, SMAP, SMOS, and ASCAT) are
30 often used to evaluate LSM at large spatial scales. Many of these products differ in
31 terms of the satellite sensors and start of operations, and are subject to data gaps,
32 coarse resolution and limited coverage (Beck et al., 2021). We use the Soil Water
33 Index (SWI) products (soil moisture expressed in percentage degree of saturation)
34 from the fusion of Sentinel-1 C-SAR and Metop ASCAT sensors to evaluate NOAH-
35 MP model at grid scales. The product is produced from ASCAT surface soil moisture
36 (SSM) using a two-layer water balance model that relates the surface and profile soil
37 moisture as a function of time (Wagner, 1999; Albergel et al., 2008). We employ the



1 operational ASCAT SWI provided at eight different time characteristics (taken as the
2 soil depths), 1km resolution and daily mean values, from 2015 to 2022. The product is
3 archived by Copernicus Land Service and has been well validated in previous studies
4 (e.g. Albergel et al., 2012; Paulik et al., 2014; Beck et al., 2021).

5

6 2.7 Analysis

7 2.7.1 Model evaluation using in situ data

8 The half-hourly or hourly station data and model outputs for each grid cell are
9 aggregated to daily averages to be consistent throughout the analysis. Then, for each
10 validation site and variable, the daily mean values from the respective model grid cell
11 are extracted at the model resolution. The daily values of soil temperature and
12 volumetric water content (both at topsoil 0-7cm) layer are compared against the in situ
13 measurements. The model estimated values are then evaluated using the Root Mean
14 Square Deviation (RMSD), Percent Bias (PBIAS) and Pearson's Correlation
15 Coefficient (R).

16

17 2.7.2 Model evaluation using satellite data

18 Given the limited number of in situ sites and scale differences between point
19 observations and model grid resolution, the general interpretation of model
20 performance across landscapes should be treated with care. However, the use of
21 satellite data is a standard practice and a pragmatic way of evaluating model outputs
22 of soil moisture over large spatial scales (He et al., 2023), notwithstanding the inherent
23 uncertainty (e.g. coarse resolution and data gaps) of the satellite products. We
24 evaluate NOAH-MP soil moisture output against ASCAT SWI for the surface and
25 subsurface layers. To make the NOAH-MP soil moisture comparable with ASCAT SWI,
26 we derive the grid-scale Relative Soil Moisture (RSM) to vary between 0 for wilting
27 point and 1 for saturation (e.g. Samaniego et al., 2018)

$$28 \quad RSM_{i,j,k} = \left(\frac{\theta_{i,j,k} - \theta_{wilt,i,j}}{\theta_{sat,i,j} - \theta_{wilt,i,j}} \right) \times 100 \quad 3,$$

29 Where $\theta_{i,j,k}$ is the simulated volumetric water content, θ_{sat} and θ_{wilt} are the soil
30 moisture at saturation and wilting point, respectively (Figure 3). We obtain RSM values
31 for both the surface and subsurface soil layers. For the surface, ASCAT SWI-002 data,
32 which imply the surface soil moisture conditions, are contrasted against the derived
33 RSM values for the topmost soil depths of 3.5 cm. The subsurface RSM values are
34 taken as the mean aggregates of the first three model layers, and are evaluated
35 against ASCAT SWI-100. Similar metrics used for point-scale evaluation (see Section



1 2.7.1) are also calculated at grid scale between the reference datasets and model
2 outputs for selected dry (2018) and normal (2019) years.

3

4 2.7.3 Soil moisture drought analysis

5 We also analyse the potential of NOAH-MP for monitoring the evolution of soil moisture
6 drought across the domain. Since the west-central European summer drought of 2018
7 was an exceptional event in terms of hydrological extremes across Ireland (Met
8 Éireann Report, 2018; Falzoi et al., 2019; Moore, 2020; Ishola et al., 2022), we
9 evaluated the model over this period. We apply grid-scale cumulative RSM values
10 integrated over three topmost soil layers (0-100 cm) (Section 2.7.2), due to its simplicity
11 and ease in quantifying and interpreting available soil water. In principle, RSM is an
12 important drought indicator, particularly at short-time scales, and analogous to the
13 widely used Soil Moisture Index (SMI) for drought monitoring at different spatial scales
14 (Samaniego et al., 2018; Grillakis, 2019).

15 To characterise soil moisture drought, percentiles of RSM values per grid cell are
16 calculated based on 7-day windows from June to August for the climatology period
17 2009 - 2022. This amounts to 98 samples (7 days x 14 years) as input per window. For
18 individual model experiments, STATSGO and SOILGRIDS, the derived spatial RSM
19 percentiles per day in each window are then classified into different drought categories
20 (Table 5), following Xia et al. (2014). These categories are currently being used by U.S.
21 Drought Monitor (USDM) for operational and regionally specific drought monitoring
22 (Svoboda et al., 2002).

23

24 3. Results

25 First, we present the analysis of ERA5-Land total annual precipitation in comparison
26 with station data, to illustrate the level of uncertainty in input meteorology. Figure 4
27 shows that the seasonal variations and total annual cumulative of precipitation are
28 reasonably replicated across the selected stations, and for different weather conditions,
29 including the extended period of no rainfall in 2018 summer (Figure 4 f).

30 3.1 Model evaluation: Soil moisture

31 Using station observations

32 The results of model simulations of volumetric water content (VWC in $\text{m}^3 \text{m}^{-3}$) for both
33 STATSGO and SOILGRIDS are presented. Figures 5 and A1 illustrate the temporal
34 comparisons and error statistics of VWC, respectively. **It is important to note that we**
35 **are comparing a model areal grid to a measurement point, which are assumed to be**
36 **equivalent.** The simulations are in closer agreement with the observed VWC at Athenry,
37 **Claremorris** and Johnstown Castle with the lowest error statistics (RMSE $\approx 0.1 \text{ m}^3 \text{ m}^{-3}$



1 ³, PBIAS < 25%) relative to other stations (Figure A1). The lowest model performance
2 occurs at Dunsany, Valentia and Dripsey, with RMSD > 0.15 m³ m⁻³, PBIAS > 30%.
3 The Pearson's correlation is generally high, above 0.8, across the measurement sites
4 except for Ballyhaise and Claremorris. Both experiments broadly underestimate the
5 observed VWC values, but the model bias is lower in the STATSGO than the
6 SOILGRIDS experiment, consistent across the stations (Figure A1). These dry biases
7 (0.15 - 0.4 m³ m⁻³) are broadly dominated in autumn and winter during which the VWC
8 values are higher or soil is assumed to be relatively wetter (Figure 5 a-f), except at
9 Dripsey where the dry biases are systematic throughout the years (Figure 5g).
10 Conversely, in summer where soil moisture conditions tend to dry in response to
11 atmospheric changes (e.g. higher global solar radiation and evaporation), VWC
12 temporal patterns are adequately captured by both model experiments (biases are less
13 than 0.1 m³ m⁻³), including the 2018 exceptionally dry summer soil moisture content
14 (Figure 5f). The differences between STATSGO and SOILGRIDS are relatively small
15 (< 0.05 m³ m⁻³) across the year(s).

16 Figure 5 (boxplot) further illustrates the summary statistics and spread of model
17 simulations and observed VWC. The mean of observed VWC (≈0.3 m³ m⁻³) is better
18 captured in STATSGO than the SOILGRIDS, particularly at Athenry, Ballyhaise,
19 Claremorris and Johnstown Castle. However, with the mean of observed VWC
20 exceeding this value, both experiments lead to significant underestimation of VWC, as
21 evident at Dunsany, Valentia and Dripsey.

22 Overall, the model experiments **closely replicate** both the mean and variance of the
23 measured surface VWC values at Athenry, Claremorris and Johnstown Castle
24 locations, where the soils are either well- or imperfectly-drained (Figure 1a).

25

26 *Using reference ASCAT satellite SWI data*

27 The selected measurement stations are well distributed and represent different soil
28 moisture regimes across Ireland (Figure 1a). However, given the relatively small
29 number of stations, generalizing the results to the entire domain may be erroneous.

30 Instead, model grid cells are individually evaluated against **the reference ASCAT**
31 **satellite data**. Figure 6 shows the results of all Ireland grid-scale model evaluation of
32 daily derived RSM values against the reference SWI at the surface and subsurface for
33 2018 dry and 2019 normal years. Median metrics for each soil texture category in
34 STATSGO and SOILGRIDS are presented in Tables 5 and 6.

35 As shown in Figure 6 (top) for the 2018 dry year, model performance is broadly better
36 for STATSGO than for SOILGRIDS, with lower median (black crossbar); RMSD of
37 around 0.015%, PBIAS of 1% in magnitude of ASCAT SWI, for both surface and



1 subsurface RSM grid values. While the Pearson's R statistic (median around 0.85) for
2 STATSGO and SOILGRIDS is comparable for the surface layer, the SOILGRIDS
3 experiment produces a higher R value in the subsurface layer during the dry year. For
4 the 2019 normal year (Figure 6, bottom), the spatial distribution of error statistics at
5 the surface layer is nearly similar for both experiments, with median RMSD of 0.015 %,
6 PBIAS of around 6 % (1 % for SOILGRIDS) and R of 0.73. At the subsurface layer,
7 SOILGRIDS produces better results than STATSGO with lower RMSD (0.01 %) and
8 PBIAS (6%) distributions and higher R statistics (median around 0.76).

9 The extended tails (positive/negative in PBIAS and lower/higher in RMSD and R) in
10 the density distribution indicate a relatively small number of isolated (spatial) grid cells
11 with larger error statistics. Given that the Loam (L) and Sandy Loam (SL) soils
12 represent the largest proportion of grid cells across the study domain and are relatively
13 comparable in terms of spatial coverage in STATSGO and SOILGRIDS (Table 2), the
14 error statistics for these soil texture categories are explained here. For 2018, results
15 show that both experiments produce lower RMSD and PBIAS error statistics for SL
16 than L at the surface layer (Table 5). Whereas at the subsurface layer, SOILGRIDS
17 perform better than STATSGO for both soil categories. For the 2019 normal year
18 (Table 6), STATSGO gives lower RMSD and PBIAS error statistics than SOILGRIDS
19 at the surface layer. Overall, model performs better over L soil type than SL based on
20 the lower PBIAS and higher R values. The RMSD and R statistics are relatively
21 comparable at the subsurface layer for both the STATSGO and SOILGRIDS
22 simulations and for L and SL soil categories. However, STATSGO produces lower
23 PBIAS statistics than SOILGRIDS in L soil. Generally, the error statistics are lower in
24 L than SL soil at the sub surface layer.

25 The spatial characteristics of model surface RSM annual mean bias relative to the
26 reference datasets for the years 2018 and 2019 are illustrated in Figure 7 a-j, and the
27 long-term seasonal characteristics of topsoil VWC between the experiments are shown
28 in Figure A2. Wet biases are predominant in the north, characterised as SL in
29 STATSGO and SOILGRIDS; towards the south and southeast of the domain, the
30 results shift towards a dry bias, mostly in areas represented by L soils. While the spatial
31 coverage of model bias is consistent for both experiments and the years, the dry bias
32 in both years is more pronounced in SOILGRIDS than STATSGO in the affected areas.
33 Conversely, the wet bias is more widespread in STATSGO than SOILGRIDS.

34

35 3.2 Model evaluation: Soil temperature

36 Figure 8 (a-g) illustrates model comparisons against the reference station
37 measurements of top soil temperature, while Figure A3 shows the associated



1 evaluation results. Generally, the error statistics (RMSD and PBIAS) for both the
2 STATSGO and SOILGRIDS experiments are low, and R values are high (above 0.9
3 across all sites). The model errors are better RMSD < 3 K and PBIAS < 1% in Athenry,
4 Dunsany, Valentia and Johnstown Castle, than in Ballyhaise, Claremorris and Dripsey
5 where the errors exceeded these values. Comparatively, SOILGRIDS leads to a
6 slightly better model performance than STATSGO across the sites.
7 Additionally, the soil temperature increases from around 280 K in winter to a peak of
8 about 297 K in summer, and up to 300 K during the extreme hot and dry summer of
9 2018 (e.g. Johnstown Castle) (Figure 8f). The spread and variance of the observed
10 soil temperature are reasonably replicated by both experiments (Figure 8, bottom).
11 Whereas the mean of observed soil temperature, which is approximately 285 K, is
12 systematically underestimated by 1 K to 3 K across stations, the peak values in the
13 mid-summer months are well captured by the experiments (Figure 8a-g).
14 Overall, both STATSGO and SOILGRIDS produce soil temperature profiles that are
15 close, but significantly different ($p\text{-value} < 2.2 \times 10^{-16}$) and are comparable with
16 observations for the study year(s) and locations.
17 **Given the reasonable model performance across the selected locations, the grid-scale**
18 **model differences between STATSGO and SOILGRIDS in the absence of satellite**
19 **reference observations, is further examined (Figure 9).** The spatial differences of
20 surface soil temperature are based on the seasonal long-term climatology from 2009
21 to 2022. In response to seasonal variations in global solar radiation and VWC, winter
22 shows the lowest soil temperature (Figure 9 a,e,i), whereas summer is characterised
23 by the highest soil temperature (Figure 9 c,g,k). The highest soil temperature in
24 summer are widespread mostly over Loam soil in the south and southeast of the study
25 domain. The south and east are seasonally drier, experiencing lower rainfall and soil
26 water deficits in summer (Figures 1a and A4). In other seasons, the spatial
27 characteristics are irregular. This spatiotemporal evolution of the soil temperature
28 characteristics is consistent in both STATSGO and SOILGRIDS model experiments.
29 That is, both soil texture maps produce soil temperature differences that are negligible
30 mostly in the south and southeast dominated by Loam soils (Figure 9 i-l). However,
31 STATSGO broadly shows a cold soil temperature bias in Clay and Clay Loam soils,
32 and a small warm bias over Sandy Loam in the northern border and southwest, relative
33 to SOILGRIDS. The areas of cold and warm biases broadly coincide with areas of wet
34 and dry biases of STATSGO VWC in comparison with SOILGRIDS (Figure A2).

35

36 3.3 Spatial and temporal evolution of soil moisture drought



1 Figure 10 illustrates the spatial characteristics of 0-100 cm RSM percentiles for
2 selected days during summer 2018. The days are used to denote the start, peak and
3 end of summer water deficits (Figure 4 f). For the first 7-day window ending 07 June,
4 the southeast and east of Ireland broadly show low drought intensity D0-D1
5 (abnormal/moderate) in STATSGO, relative to SOILGRIDS with severe drought D2
6 category. Both experiments are largely consistent in other areas of the study domain.
7 For example, the major land areas in the north of the island are characterised as
8 severe drought D2, and D0-D1 in the midlands and west of Ireland. However, the D0-
9 D1 categories are more spatially widespread across the midlands and west in
10 SOILGRIDS than in STATSGO.

11 By the middle of summer 2018 (sixth week ending 12 July), the entire Ireland is
12 dominated by exceptional drought D4 category in STATSGO, except for the land areas
13 in the north where the D2 category is sustained over time. These patterns are
14 consistent in SOILGRIDS except for some areas with higher intensity. For example,
15 the drought category in the southeast of Northern Ireland shifts from D2 in STATSGO
16 to D3-D4 (extreme and exceptional) categories, and from D2-D3 (severe and extreme)
17 category in the southwest of Ireland to D3-D4 drought categories in SOILGRIDS.

18 Whereas the soil water deficits appear to have improved by the end of summer (week
19 13 ending 30 August), the landscapes are still largely under different levels of soil
20 dryness. For example, in STATSGO, moderate drought D1 category broadly
21 dominates the Loam soil texture areas in the midlands, south and southeast of Ireland,
22 while a mix of drought D1-D4 categories dominates the west and southwest of the
23 country. These patterns are consistent in SOILGRIDS, but areas in the northern border,
24 west and southwest with a sustained D3-D4 categories are wider in SOILGRIDS than
25 STATSGO.

26 Figure 11 illustrates the time-areal coverage cross-section of various drought
27 categories over the domain during the summer period 2018, based on RSM percentiles.
28 While the landscapes are already under soil water deficits by the start of summer in
29 June, the largest areal coverage (about 70 % in STATSGO and 80 % in SOILGRIDS)
30 is dominated by low drought intensities (D0-D2). Approximately 10 % of the domain is
31 characterised by extreme and exceptional D3-D4 drought, up to the end of June. The
32 drought intensifies effectively from late June, with higher areal coverage of D4 category
33 of more than 80 %, extending for several days in STATSGO. This is similar in
34 SOILGRIDS, however, days in July that show recovery based on a reduced areal
35 coverage of D3-D4 category in STATSGO, show high coverage of the same intensities
36 in SOILGRIDS. At the start of August, the areal coverage of high intensity D3-D4
37 drought has effectively dropped, compensated by an increase in the spatial coverage



1 of D0-D2. In the last week of August, the areal coverage of D0-D1 is higher (about
2 80 %) relative to other drought categories.

3

4 **4. Discussions**

5 4.1 Effects of soil hydrophysical properties on simulated soil hydrothermal regimes.

6 As a consequence of misrepresentation of soil texture classes in LSMs, soil
7 hydrophysical properties are expected to influence model simulations of changes in
8 soil moisture content and soil temperature across space and time. In this study, we
9 investigate the difference between two commonly used global soil texture maps
10 implemented in NOAH-MP land surface model, namely STATSGO and SOILGRIDS.
11 The impact of using the default look-up table and PedoTransfer Functions (PTFs) to
12 prescribe grid-scale soil properties (e.g. porosity, field capacity, wilting point, hydraulic
13 conductivity, etc.), on simulated surface and subsurface soil hydrothermal changes
14 during normal period and extremely dry year is further evaluated. **The role of these
15 properties, particularly the field capacity – a measure of water retained in the soil at
16 the pressure of -0.33 bar, after excess rain water has drained off, are critical in LSMs
17 that simulate soil hydrophysical processes and interactions with the atmosphere.**

18 At point-scale, the results reveal model differences between dry and wet soil moisture
19 regimes and are able to fairly replicate the measured values of soil moisture and soil
20 temperature across a variety of weather conditions, including during extreme water
21 shortage. While STATSGO is closer to observations than SOILGRIDS, the model
22 errors between these data sources are marginal but statistically significant (p -value <
23 2.2×10^{-16}) for both variables, notwithstanding the difference in soil physics. Despite
24 misrepresentation of soil texture class by both sources, for example at Johnstown
25 Castle (Table 1), the model does reasonably well. **However, for a relatively wet site
26 (e.g. Dripsey) where the soil texture class is accurately represented in both soil
27 databases, the model systematically underestimates soil moisture content (Figures 5g
28 and A1).** This illustrates that the soil-induced model uncertainty is rarely linked to
29 misrepresentation of soil texture class, but to the soil physics and the prescribed soil
30 hydrophysical parameters.

31 For example, the field capacity (FC) value reported for Johnstown Castle (Table 1) is
32 $0.32 \text{ m}^3 \text{ m}^{-3}$ (Ishola et al., 2020), which is close to the values employed in STATSGO
33 and SOILGRIDS, and consistent with station measurements (Figures 3 and 4).
34 However, the observed FC value in Dripsey is approximately $0.42 \text{ m}^3 \text{ m}^{-3}$ (Table 1),
35 which contrasts the values of approximately $0.31 \text{ m}^3 \text{ m}^{-3}$ used in the models (Figure 3
36 and 4 bottom) and values reported in Liu et al. (2012) and Ishola et al. (2020) for this
37 site. The bias in FC limits the ability of the soil to increase the memory of the stores,



1 resulting in systematic bias in the simulated VWC. To illustrate the role of prescribed
2 FC values for Dripsey, the simulated VWC for a neighboring grid cell with a FC of 0.412
3 $\text{m}^3 \text{m}^{-3}$ and similar weather condition is evaluated against the measured VWC (Figure
4 12). A higher FC clearly results in higher VWC values, reducing the bias between
5 observations and STATSGO by more than 50 % of the value at Dripsey. In contrast,
6 the maximum FC derived from SOILGRIDS across the domain is 0.34 $\text{m}^3 \text{m}^{-3}$ (Figure
7 3), which still lies around the default value, and is not in a proximal grid location to
8 Dripsey site. Hence, using the same grid cell as above, the SOILGRIDS with PTFs fall
9 short of this illustration and consequently fail to improve the simulated VWC.

10 At grid-scale, the STATSGO and SOILGRIDS soil texture data are evidently different,
11 particularly in the north, west and southwest of Ireland (Figure 2). Notably, the
12 STATSGO data represents smaller soil grain sizes in most of these areas, relative to
13 SOILGRIDS. This results in higher values of soil hydrophysical properties in STATSGO,
14 including porosity and field capacity (Figure 3). The increasing grain size leads to wet
15 and cold biases in STATSGO, relative to SOILGRIDS in these notable areas (Figures
16 7, 9 and A2). Similar to our results, It has been demonstrated that a reduction in soil
17 grain size (e.g. Loam to Sandy Loam) leads to dry and hot biases (decrease in latent
18 heat flux and increase in sensible heat flux) between two global soil datasets (Dennis
19 and Berbery, 2021).

20

21 While the choice of PTFs is critical in model simulations of soil water fluxes
22 (Weihermüller et al. 2021), the default Saxton and Rawls (2006) soil physics produce
23 properties that are very close to using the look-up table in NOAH-MP model. One
24 reason for this similarity is that the SOILGRIDS sand and clay compositions produce
25 Loam and Sandy Loam soil texture, based on USDA classes, and these coincide with
26 FAO/STATSGO in space with nearly the same areal coverage (Figure 2 and Table 2).
27 Another reason for similar soil properties between the PTFs and look-up table, is the
28 default PTFs coefficients which are derived based on USDA soil samples (Saxton and
29 Rawls, 2006) and may be inaccurate for the study domain; the empirically-derived look-
30 up table is also based on soil samples in the US. The net effect of similar but inaccurate
31 soil properties is the significant under-representation of soil hydrothermal regimes in
32 wet soils as illustrated in Figures 5 and 7. This aligns with Vereecken et al. (2010) who
33 demonstrated that PTFs are highly accurate over the areas for which they have been
34 developed, but have limited accuracy if transferred outside these areas.

35 The overall results indicate that there is a major impact of under-represented soil
36 hydrophysical parameters, particularly in relatively wet sites, regardless of the source
37 of global soil texture map and soil physics option implemented in NOAH-MP. The



1 discrepancies between STATSGO and SOILGRIDS exert great regional impacts on
2 the soil hydrothermal regimes.

3

4 4.2 Implications for regional drought monitoring

5 Soil moisture content is an essential variable in many hydrological applications and in
6 understanding the evolution and characteristics of extreme climate events such as
7 droughts. Instead of heatwaves, the study domain is rather subject to rainfall extremes
8 (Noone et al., 2017), a precursor of soil water deficits and droughts; the intensity and
9 frequency of which have been projected to increase globally and in the study domain
10 by the end of century (Seneviratne et al., 2012; Fealy et al., 2018).

11 In this study, the drought analysis are based on the cumulative RSM percentiles
12 aggregated over three uppermost soil layers (0-100 cm) for 2018 summer hydrological
13 extremes for STATSGO and SOILGRIDS (Figures 10-11). The 0-100 cm depth is
14 sufficient for drought assessment since the root zone of many crops grown across the
15 world does not surpass 1.0 m in depth (Fan et al., 2016; Grillakis et al., 2019).

16 Both STATSGO and SOILGRIDS are largely consistent in terms of the evolution of soil
17 moisture drought in space and time. However, SOILGRIDS shows higher drought
18 intensity in the many areas, relative to STATSGO. This is due to the dry bias of
19 SOILGRIDS associated with underrepresented soil hydrophysical properties and
20 simulated VWC (Figures 3 and A2). During the summer of 2018, particularly from late
21 May to late July, Ireland was reported to have experienced different degrees of
22 meteorological droughts (rainfall deficits) (Figure 4 f) ranging from dry spells to
23 absolute droughts (Met Éireann Report, 2018; Falzoi et al., 2019; Moore, 2020).
24 Meteorological droughts precede soil moisture/agricultural droughts through reduction
25 in soil water storage and available water for plant uptake, our results indicate that
26 extreme to exceptional soil moisture droughts are only effective from last week in June,
27 covering the large part of the domain by mid-July (Figure 11). During August, rainfall
28 improved soil water stores (Figure 4 f) and weakened drought conditions across much
29 of the country, particularly in the north and west (Met Éireann Report, 2018; Moore,
30 2020).

31 Overall, the discrepancies between STATSGO and SOILGRIDS impacts drought
32 characteristics mostly in space, with SOILGRIDS shifting the
33 abnormal/moderate/severe droughts in STATSGO to extreme/exceptional droughts.
34 These may result in erroneous or potential loss of vital information with dire
35 consequences on ecosystems with regards to predicting the response and productivity,
36 as drought stress has been highlighted as the primary factor limiting ecosystem
37 response and productivity (De Boeck et al., 2011).



1

2

3 **5. Conclusions**

4 In this study, the usability of two global soil datasets for representing soil processes in
5 NOAH-MP model and simulating soil hydrothermal variations and associated extremes,
6 has been evaluated across all of Ireland. Specifically, FAO/STATSGO dominant soil
7 texture categories linked to an empirically-derived soil hydrophysical properties from a
8 look-up table (default in WRF), are compared with PedoTransfer Functions (PTFs) that
9 ingest an alternative SOILGRIDS sand and clay compositions at four soil layers.
10 Through temporal comparison with in situ soil moisture and soil temperature
11 observations, it has been found that, both soil datasets can **fairly replicate** the general
12 soil hydrothermal variations. However, they under-represent the soil properties (e.g.
13 field capacity) in wet loam soil, leading to systematic dry bias in soil moisture. The
14 results have further shown that there is no distinct difference between the soil physics
15 applied to the same soil texture category in both STATSGO and SOILGRIDS. But, the
16 disparities and sensitivity to soil physics increase for different soil texture categories
17 between the datasets.

18 Through spatial comparison with satellite-based ASCAT SWI, dry bias is more
19 pronounced and widespread in the midland, south and east in SOILGRIDS, while wet
20 bias dominates the west and north. As a consequence, 2018 summer soil moisture
21 droughts broadly intensify more in SOILGRIDS than in STATSGO. **These disparities**
22 **may result in misinformation that could hamper adequate and effective preparation and**
23 **response during drought episodes.** While identifying the better soil database is not the
24 primary objective of this study, STATSGO performs slightly better than SOILGRIDS.
25 Overall, the study highlights the shortcomings of global soil databases in simulating
26 soil hydrothermal changes and underscore the need to optimize and improve global
27 soil hydrophysical properties that are ingested in LSMs for better performance.
28 Developing detailed regional soil texture properties may be more realistic and enables
29 more improvement in model simulations. Ultimately, this would advance the
30 understanding of the role of soil processes in hydrologic cycle, ecosystem productivity,
31 drought evolution, land-atmosphere interactions and regional climate.

32 A number of initiatives (e.g. Terrain-AI) has been developed to deploy soil moisture
33 measuring network across Ireland to address the lack of soil moisture observations. A
34 significant conclusion of this study is that the NOAH-MP model has shown an excellent
35 capacity to ingest better alternative soil texture data, to reduce the model biases of soil
36 hydrothermal changes and evolution of soil moisture drought. Therefore, it can be
37 applied to augment current network of sites across the country for operational modeling



1 and real-time forecasting of soil moisture conditions and drought across the domain.
2 This will support hydrometeorological monitoring similar to Global Food Awareness
3 System (GloFAS) and NASA's Short-term Prediction Research and Transition with
4 Land Information System (SPoRT-LIS).

5

6 **Code and data availability**

7 The open-source HRLDAS/NOAH-MP model is freely available on github
8 (<https://github.com/NCAR/hrldas>). The ERA5-Land hourly input meteorological forcing were
9 downloaded from the climate data store (<https://cds.climate.copernicus.eu/>). The WPS
10 geographical data were downloaded from NCAR ([https://ral.ucar.edu/model/noah-](https://ral.ucar.edu/model/noah-multiparameterization-land-surface-model-noah-mp-lsm)
11 [multiparameterization-land-surface-model-noah-mp-lsm](https://ral.ucar.edu/model/noah-multiparameterization-land-surface-model-noah-mp-lsm)). 2018 Corine land use and satellite
12 ASCAT soil water index are freely available on Copernicus Global Land Service
13 (<https://land.copernicus.eu/global/index.html>). In situ data for the selected sites were obtained
14 from Met Eireann, Ireland and from the European fluxes database cluster ([http://www.europe-](http://www.europe-fluxdata.eu)
15 [fluxdata.eu](http://www.europe-fluxdata.eu)).

16

17 **Competing interests**

18 The contact author has declared that none of the authors has any competing interests.

19

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26

27 **Author Contributions**

28 Conceptualization, K. I. and R. F.; methodology, K.I. and R.F.; software, K.I. and R. F. with
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30 resources, K.I. and R.F.; data curation, K. I.; writing—draft preparation and review, was led by
31 K. I., G. M., M.D. and R. F., with contributions from all co-authors.; visualization, K.I.;
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33 T.M.

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1 Table 1. Summary of locations of in situ measurements. The station land cover and elevation data are
 2 obtained from Met Eireann service. The station soil texture data for Johnstown Castle and Dripsey are
 3 obtained from previous work (Kiely et al., 2018; Murphy et al., 2022), and soil texture map from the
 4 Irish Soil Information System (Creamer et al., 2014) are used for the in situ Terrain-AI sites

5 Sites	6 Lon/Lat (°)	7 Elevation (m)	8 Field Capacity	9 Soil texture category		
				10 In-situ	11 STATSGO	12 SOILGRIDS
13 Athenry	14 -8.786/ 15 53.2892	16 40.0	17 -	18 Loam	19 Loam	20 Loam
21 Ballyhaise	22 -7.309/ 23 54.0513	24 78.0	25 -	26 Loam	27 Clay- Loam	28 Loam
29 Claremorris	30 -8.992/ 31 53.7108	32 68.0	33 -	34 Sandy- Loam	35 Loam	36 Loam
37 Dunsany	38 -6.660/ 39 53.5158	40 83.0	41 -	42 Loam	43 Loam	44 Loam
45 Valentia	46 -10.244/ 47 51.9397	48 25.0	49 -	50 Sandy- Loam	51 Sandy- Loam	52 Loam
53 Johnstown Castle	54 -6.505/ 55 52.2981	56 52.0	57 0.32	58 Sandy- Loam	59 Loam	60 Loam
61 Dripsey	62 -8.752/ 63 51.9867	64 190.0	65 0.42	66 Loam	67 Loam	68 Loam

28 Table 2. Percentage proportion of grids covered by soil texture categories
 29 for STATSGO and SOILGRIDS databases used.

30 Soil texture	31 STATSGO (%)	32 SOILGRIDS (%)
33 Sandy Loam	34 16.4	35 27.0
36 Loam	37 57.8	38 71.5
39 Sandy Clay Loam	40 0	41 1.4
42 Clay Loam	43 19.5	44 0.1
45 Clay	46 6.3	47 0

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1 Table 3. Summary of NOAA-MP physical options used in this study

2 Physical processes	Options
3 Vegetation	(4) Prescribed LAI + Prescribed max FVEG
4 Canopy stomatal resistance	(1) Ball-berry
5	(2) Jarvis
6 Soil moisture factor	(1) Noah
7 Runoff and groundwater	(3) Noah (free drainage)
8 Surface layer drag	(1) Monin-Obukhov
9 Radiation transfer	(3) Gap=1-FVEG
10 Snow surface albedo	(2) CLASS
11 Precipitation partition	(1) Jordan (1991)
12 Lower boundary soil	
13 temperature	(2) Soil temperature at 8m depth
14 Snow/soil temperature time	(1) Semi-implicit
15 Surface resistance	(1) Sakaguchi and Zeng (2009)
16 Soil data	(1) Dominant soil texture
17	(3) Soil composition and PedoTransfers
18 PedoTransfers	(1) Saxton and Rawls (2006)

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22 Table 4. Definitions of drought categories based on Relative Soil Moisture (RSM) percentiles

23 ID	RSM percentile	Descriptions
24 Dryness		
25 D0	≤ 30	Abnormal
26 D1	≤ 20	Moderate
27 D2	≤ 10	Severe
28 D3	≤ 5	Extreme
29 D4	≤ 2	Exceptional
30 Wetness		
31 W0	≥ 70	Abnormal
32 W1	≥ 80	Moderate
33 W2	≥ 90	Severe
34 W3	≥ 95	Extreme
35 W4	≥ 98	Exceptional

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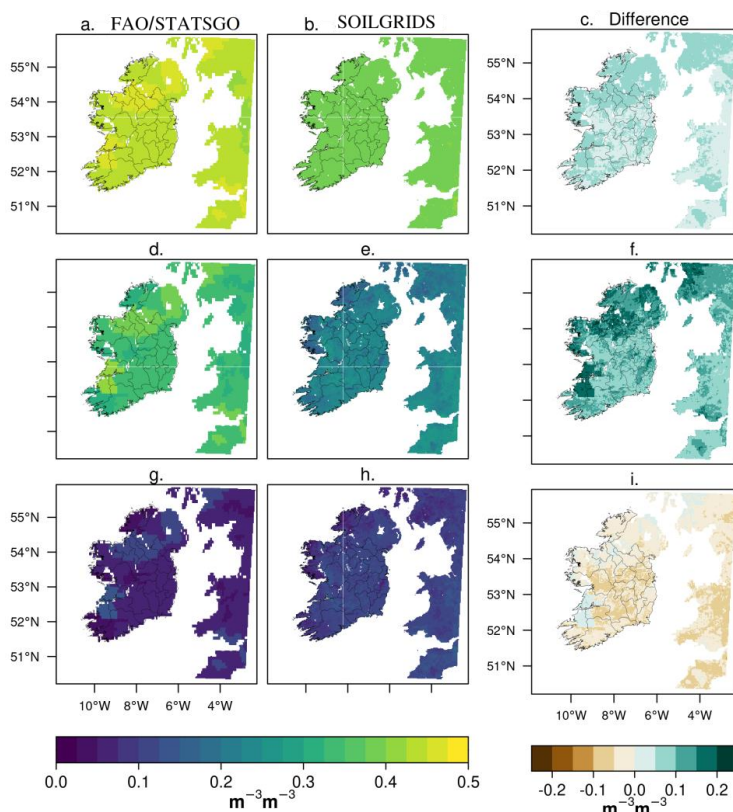
1 Table 5. Performance statistics of Relative Soil Moisture (RSM) for various soil texture categories at
 2 the topsoil (0 – 10 cm) and subsurface (0 – 100 cm) in STATSGO and SOILGRIDS for 2018 year. The
 3 errors are the median grid values. SL- Sandy Loam, L – Loam, SCL – Sandy Clay Loam, CL – Clay Loam,
 4 C – Clay.

5 Soil 6 texture	RMSD		PBIAS		R		
	STATSGO	SOILGRIDS	STATSGO	SOILGRIDS	STATSGO	SOILGRIDS	
7 Surface							
8 SL	0.016	0.016	-3.0	5.3	0.82	0.80	
9 L	0.018	0.018	-7.8	-4.5	0.84	0.84	
10 SCL	-	0.017	-	-6.0	-	0.84	
11 CL	0.016	0.016	11.0	4.6	0.79	0.86	
12 C	0.017	-	9.7	-	0.82	-	
13 Subsurface							
14 SL	0.016	0.015	2.9	3.6	0.56	0.61	
15 L	0.016	0.015	-1.9	-0.5	0.57	0.59	
16 SCL	-	0.015	-	2.0	-	0.62	
17 CL	0.014	0.015	4.5	-3.3	0.62	0.58	
18 C	0.014	-	-1.3	-	0.61	-	

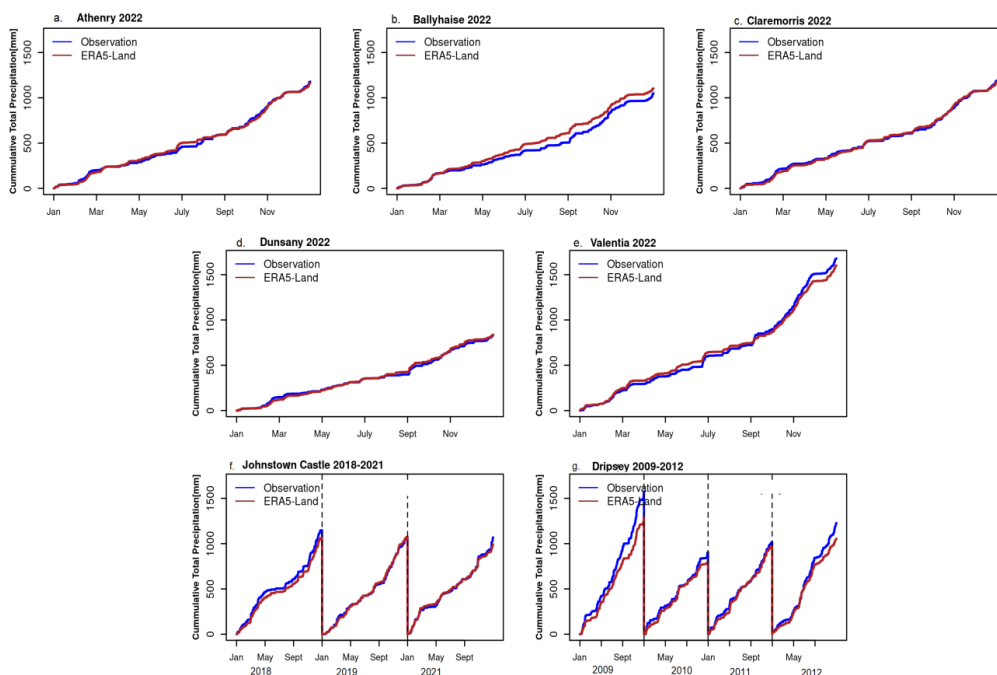
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21 Table 6. Performance statistics of Relative Soil Moisture (RSM) for various soil texture categories at
 22 the topsoil (0 – 10 cm) and subsurface (0 – 100 cm) in STATSGO and SOILGRIDS for 2019 year. The
 23 errors are the median grid values. SL- Sandy Loam, L – Loam, SCL – Sandy Clay Loam, CL – Clay Loam, C
 24 – Clay.

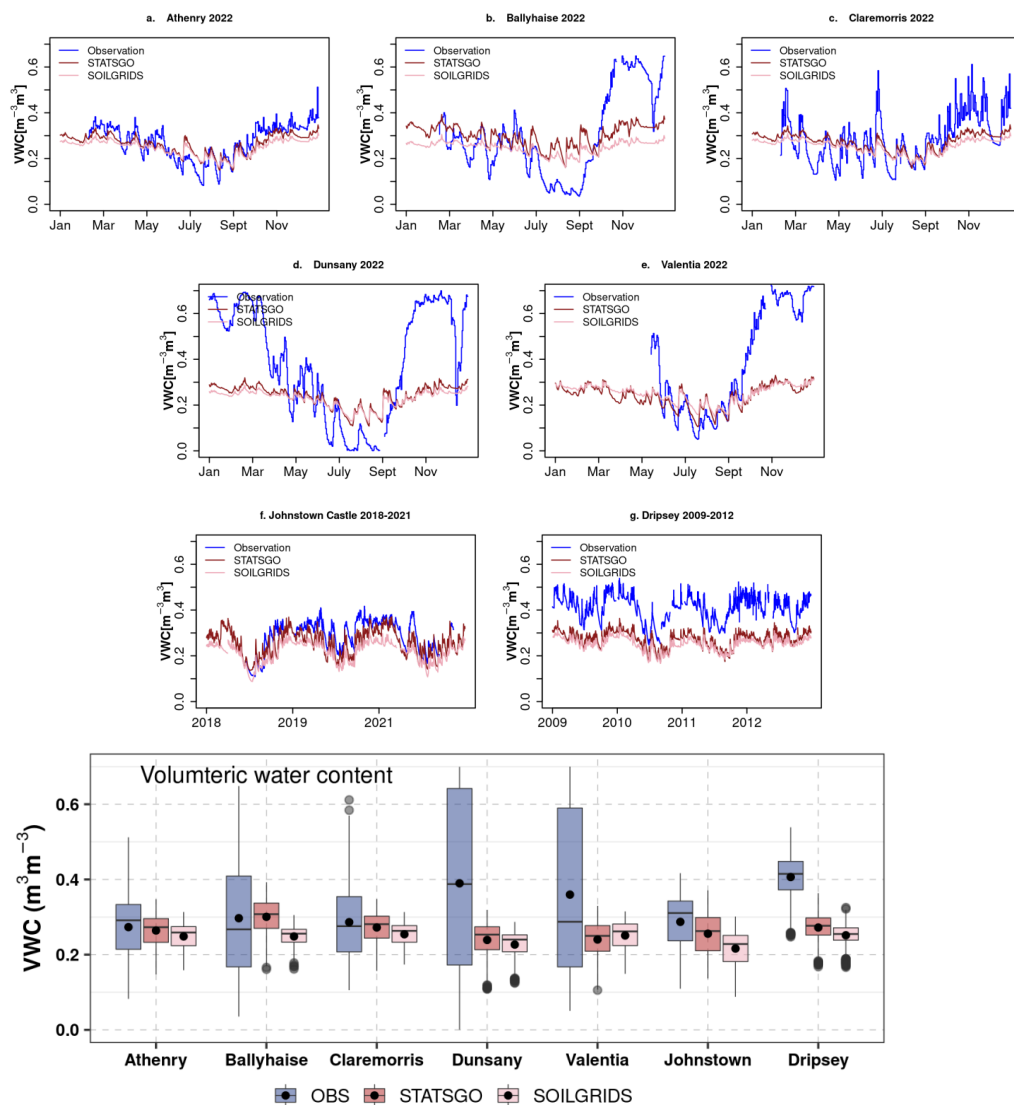
25 Soil 26 texture	RMSD		PBIAS		R		
	STATSGO	SOILGRIDS	STATSGO	SOILGRIDS	STATSGO	SOILGRIDS	
27 Surface							
28 SL	0.015	0.016	3.6	9.8	0.68	0.66	
29 L	0.016	0.016	1.2	5.2	0.72	0.71	
30 SCL	-	0.016	-	4.8	-	0.67	
31 CL	0.019	0.018	21.2	18.0	0.61	0.81	
32 C	0.019	-	20.1	-	0.79	-	
33 Subsurface							
34 SL	0.013	0.012	17.8	16.7	0.61	0.63	
35 L	0.011	0.012	13.8	16.4	0.68	0.71	
36 SCL	-	0.013	-	19.1	-	0.73	
37 CL	0.013	0.011	20.5	16.1	0.73	0.76	
38 C	0.012	-	16.1	-	0.77	-	



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2 Figure 3. Spatial characteristics of absolute and difference between STATSGO and
3 SOILGRIDS for [a-c] soil porosity, [d-f] field capacity and [g-i] wilting point.



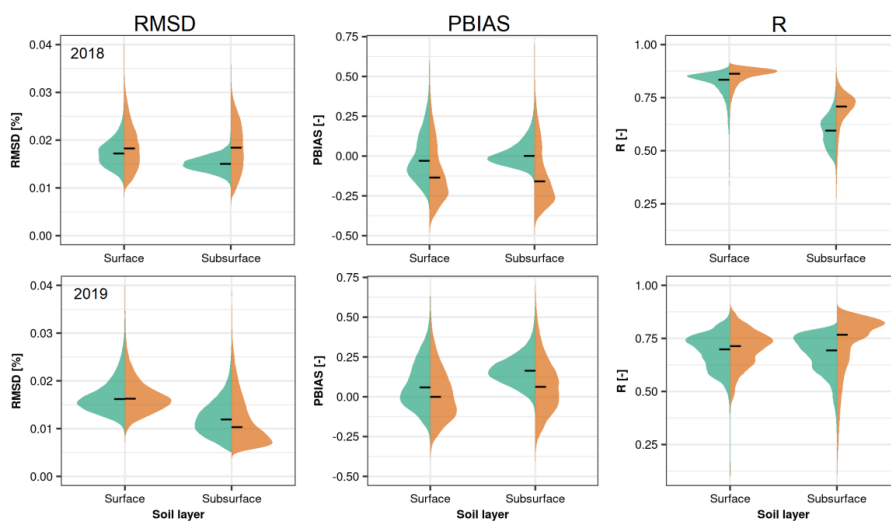
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2 Figure 4. Temporal comparisons of observed total annual cumulative precipitation at the
3 selected reference stations, against the ERA5-Land collocated grids.
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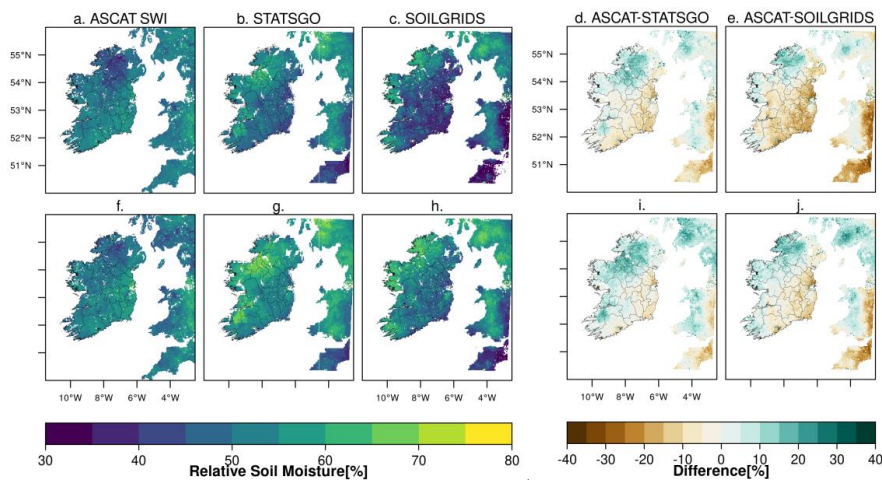
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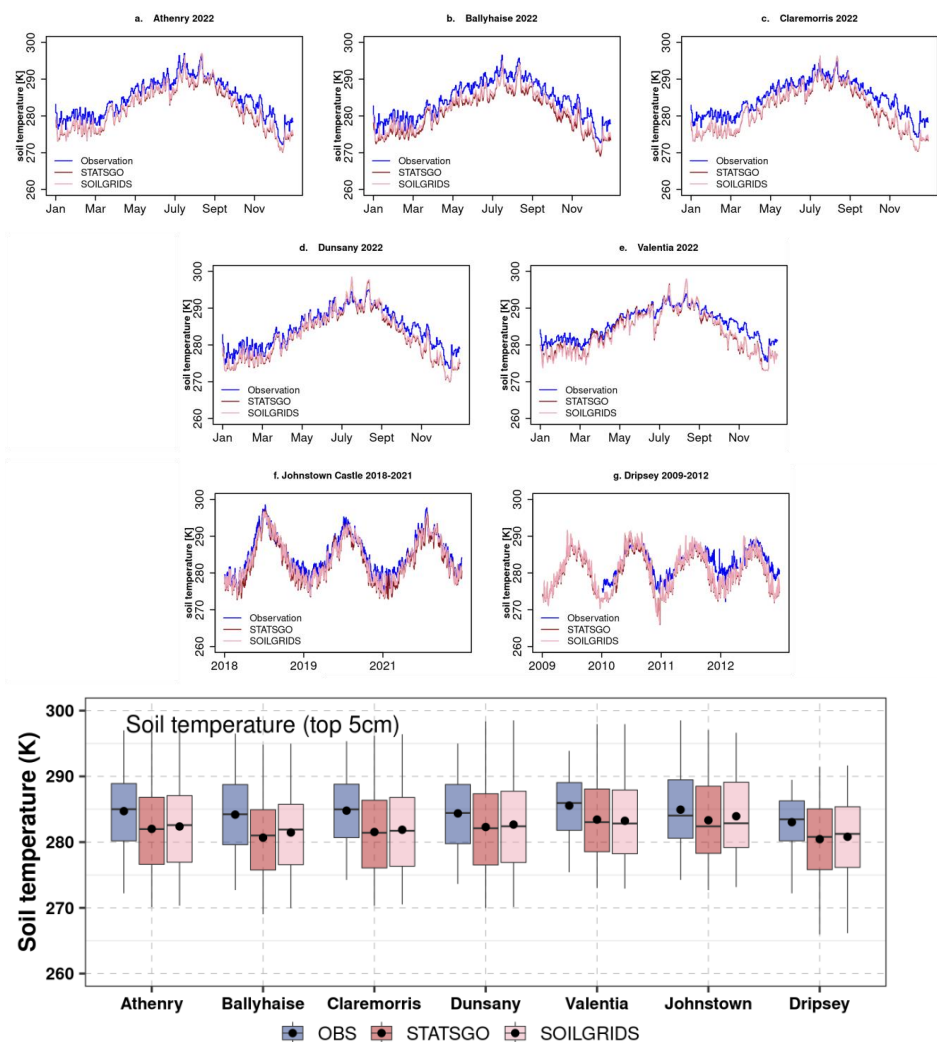
3 Figure 5. [a-g] Temporal comparisons of volumetric water contents and boxplots of data
 4 distribution, between observations and simulated values for the selected reference stations.
 5 The black dots in the boxes represent the mean values



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 Figure 6. Performance statistics for STATSGO and SOILGRIDS derived Relative Soil Moisture (RSM) values at the topsoil layer (0-7 cm) and subsurface soil layer (0-100 cm), against satellite-based ASCAT Soil Water Index (SWI), for 2018 (top) and 2019 (bottom) years. N = 131,000 cells and the black crossbars are the median values.



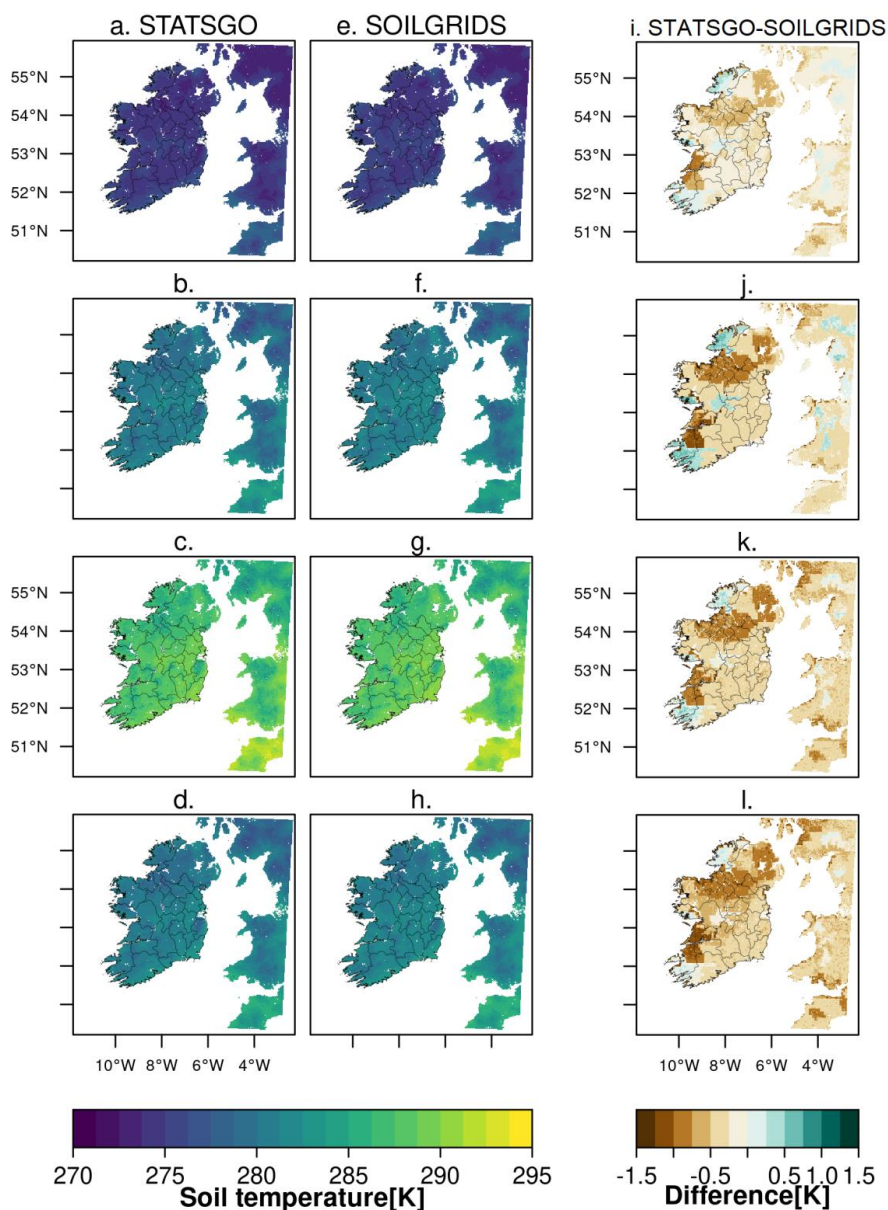
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 Figure 7. Spatial characteristics of absolute and difference between satellite-based annual ASCAT Soil Water Index (SWI) and model derived annual mean Relative Soil Moisture (RSM) at the surface, for [a-e] 2018 and [f-j] 2019 years



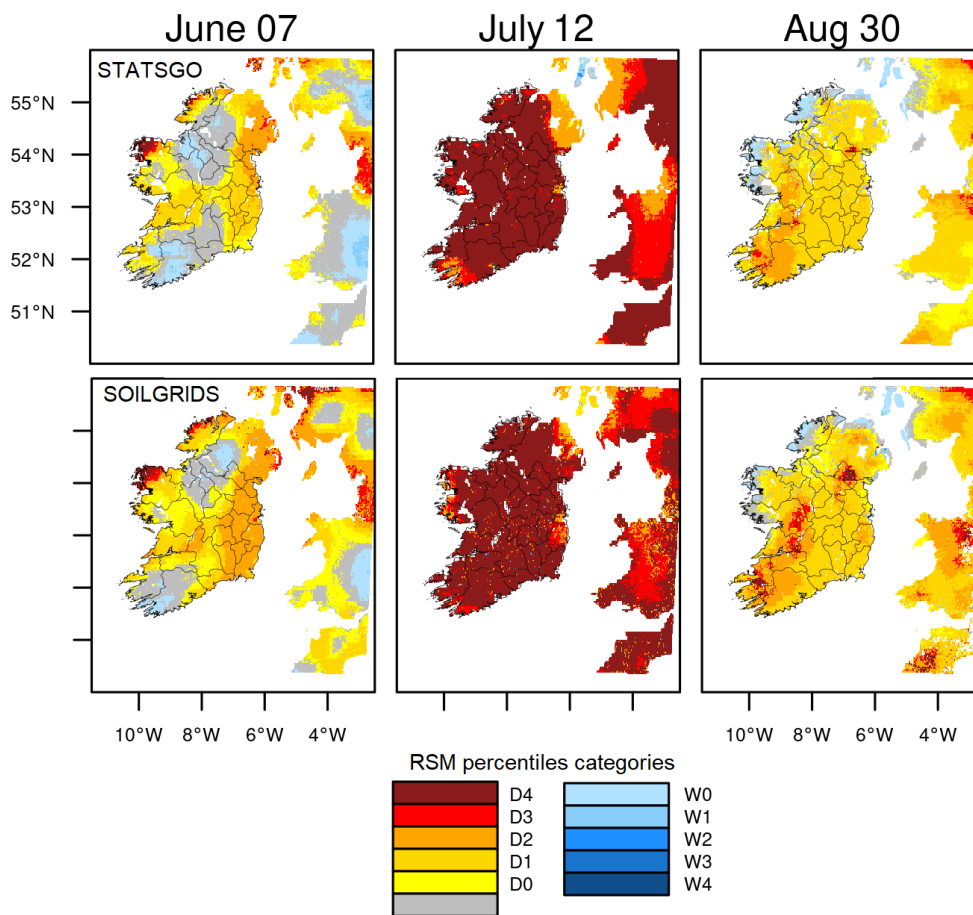
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3 Figure 8. [a-g] Temporal comparisons of soil temperature and boxplots of data distribution,
4 between observations and simulated values for the selected reference stations. The black dots
5 in the boxes represent the mean values

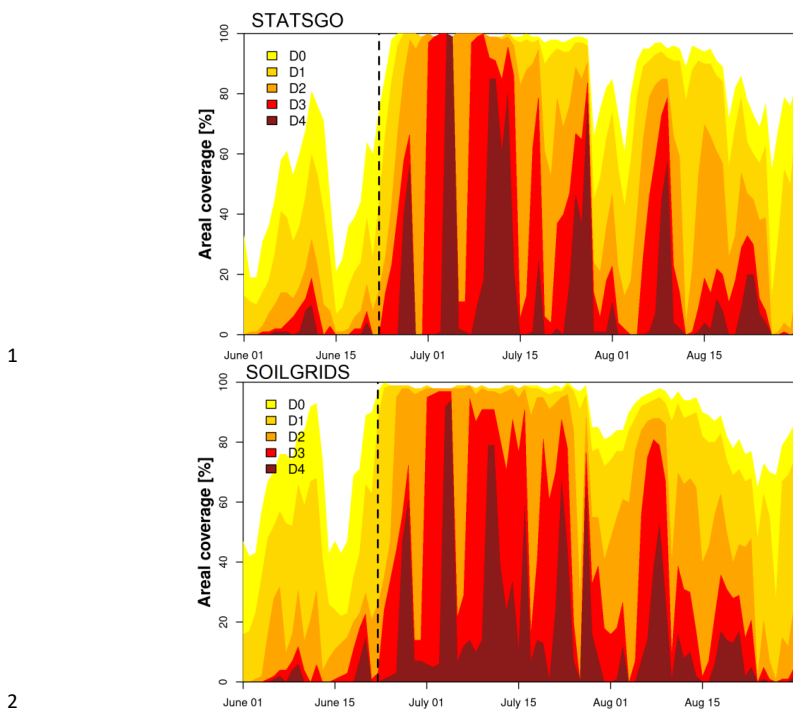
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 2 Figure 9. Spatial and seasonal characteristics of simulated top (0-7 cm) soil temperature using
 3 STATSGO [a-d], SOILGRIDS [e-h] and the difference [i-l], for the period 2009 - 2022. Rows [1-
 4 4] represent the Winter to Autumn seasons in that order.
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 3 Figure 10. Spatial characteristics of soil moisture drought categories derived using 0 – 100 cm
 4 Relative Soil Moisture percentiles for STATSGO [top] and SOILGRIDS [bottom] for 2018
 5 summer. D0-D4 represents abnormally dry, moderate, severe, extreme and exceptional
 6 droughts, while W0-W4 is the corresponding wetness categories.
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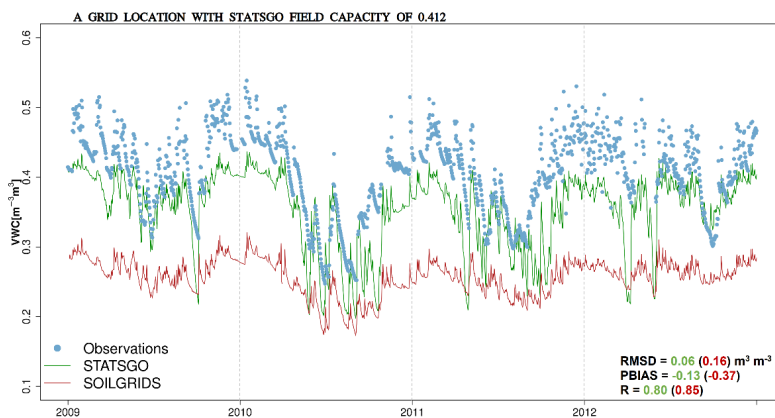
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4 Figure 11. Time-areal coverage cross-section of drought evolution based on daily 0 – 100 cm
 5 Relative Soil Moisture (RSM) percentiles during 2018 summer for STATSGO [top] and
 6 SOILGRIDS [bottom]. D0-D4 represents abnormally dry, moderate, severe, extreme and
 7 exceptional droughts. The dashed vertical lines represent the effective start of severe to
 8 exceptional droughts.

9

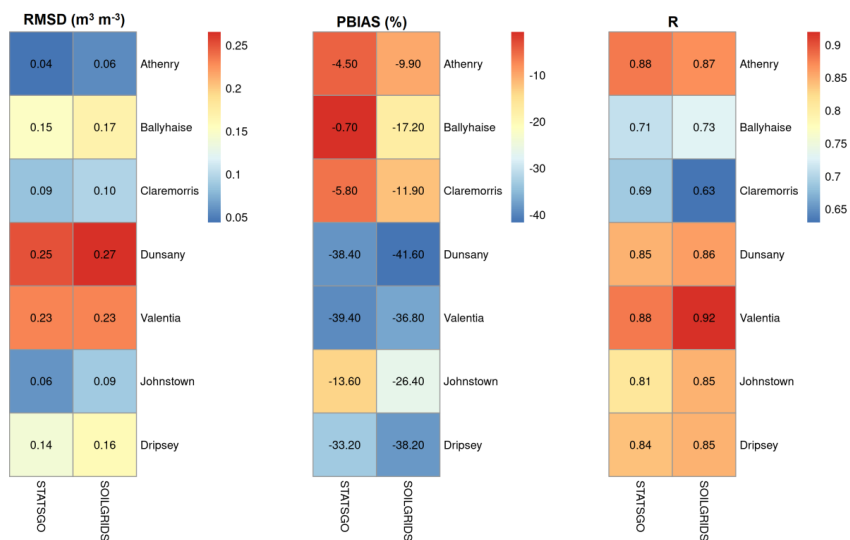


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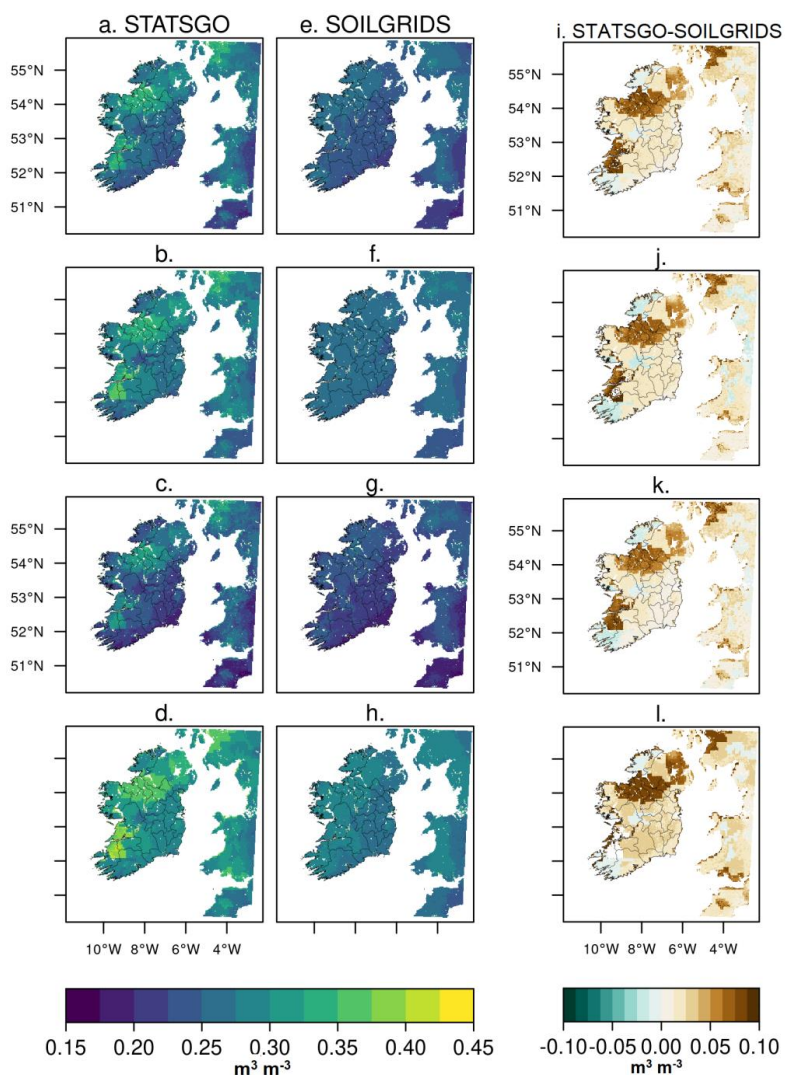
11 Figure 12. Temporal comparisons of observed volumetric water content (VWC) at Dripsey
 12 site, against the simulated values for a nearby grid location with field capacity of $0.412 \text{ m}^3 \text{ m}^{-3}$.

13

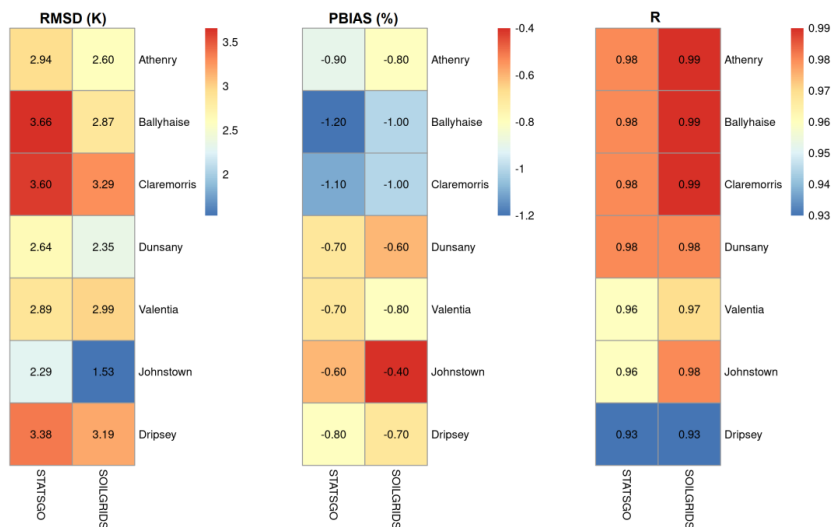
14 Appendix



1
 2 Figure A1. Error statistics of volumetric water contents between observations and model
 3 experiments for the selected reference stations.



1
 2 Figure A2. Spatial and seasonal characteristics of simulated top soil (0-7 cm) volumetric water
 3 content (VWC) using STATSGO [a-d], SOILGRIDS [e-h] and the difference [i-l], for the period
 4 2009 - 2022. Rows [1-4] represent the Winter to Autumn seasons in that order
 5



1
 2 Figure A3. Error statistics of soil temperature between observations and model experiments
 3 for the selected reference stations.
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