<table>
<thead>
<tr>
<th><strong>Title</strong></th>
<th>High-resolution gridded datasets of hydro-climate indices for Ireland</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Author(s)</strong></td>
<td>Werner, Christopher; Nolan, Paul; Naughton, Owen</td>
</tr>
<tr>
<td><strong>Publication Date</strong></td>
<td>2019-01</td>
</tr>
<tr>
<td><strong>Publisher</strong></td>
<td>Environmental Protection Agency</td>
</tr>
<tr>
<td><strong>Link to publisher's version</strong></td>
<td><a href="http://www.epa.ie/pubs/reports/research/water/research267.html">http://www.epa.ie/pubs/reports/research/water/research267.html</a></td>
</tr>
<tr>
<td><strong>Item record</strong></td>
<td><a href="http://hdl.handle.net/10379/15941">http://hdl.handle.net/10379/15941</a></td>
</tr>
</tbody>
</table>
High-resolution Gridded Datasets of Hydro-climate Indices for Ireland

Authors: Christopher Werner, Paul Nolan and Owen Naughton
ENVIRONMENTAL PROTECTION AGENCY
The Environmental Protection Agency (EPA) is responsible for protecting and improving the environment as a valuable asset for the people of Ireland. We are committed to protecting people and the environment from the harmful effects of radiation and pollution.

The work of the EPA can be divided into three main areas:

Regulation: We implement effective regulation and environmental compliance systems to deliver good environmental outcomes and target those who don’t comply.

Knowledge: We provide high quality, targeted and timely environmental data, information and assessment to inform decision making at all levels.

Advocacy: We work with others to advocate for a clean, productive and well protected environment and for sustainable environmental behaviour.

Our Responsibilities

Licensing
We regulate the following activities so that they do not endanger human health or harm the environment:
- waste facilities (e.g. landfills, incinerators, waste transfer stations);
- large scale industrial activities (e.g. pharmaceutical, cement manufacturing, power plants);
- intensive agriculture (e.g. pigs, poultry);
- the contained use and controlled release of Genetically Modified Organisms (GMOs);
- sources of ionising radiation (e.g. x-ray and radiotherapy equipment, industrial sources);
- large petrol storage facilities;
- waste water discharges;
- dumping at sea activities.

National Environmental Enforcement
- Conducting an annual programme of audits and inspections of EPA licensed facilities.
- Overseeing local authorities’ environmental protection responsibilities.
- Supervising the supply of drinking water by public water suppliers.
- Working with local authorities and other agencies to tackle environmental crime by co-ordinating a national enforcement network, targeting offenders and overseeing remediation.
- Enforcing Regulations such as Waste Electrical and Electronic Equipment (WEEE), Restriction of Hazardous Substances (RoHS) and substances that deplete the ozone layer.
- Prosecuting those who flout environmental law and damage the environment.

Water Management
- Monitoring and reporting on the quality of rivers, lakes, transitional and coastal waters of Ireland and groundwaters; measuring water levels and river flows.
- Monitoring and reporting on Bathing Water Quality.

Monitoring, Analysing and Reporting on the Environment
- Monitoring air quality and implementing the EU Clean Air for Europe (CAFÉ) Directive.
- Independent reporting to inform decision making by national and local government (e.g. periodic reporting on the State of Ireland’s Environment and Indicator Reports).

Regulating Ireland’s Greenhouse Gas Emissions
- Preparing Ireland’s greenhouse gas inventories and projections.
- Implementing the Emissions Trading Directive, for over 100 of the largest producers of carbon dioxide in Ireland.

Environmental Research and Development
- Funding environmental research to identify pressures, inform policy and provide solutions in the areas of climate, water and sustainability.

Strategic Environmental Assessment
- Assessing the impact of proposed plans and programmes on the Irish environment (e.g. major development plans).

Radiological Protection
- Monitoring radiation levels, assessing exposure of people in Ireland to ionising radiation.
- Assisting in developing national plans for emergencies arising from nuclear accidents.
- Monitoring developments abroad relating to nuclear installations and radiological safety.
- Providing, or overseeing the provision of, specialist radiation protection services.

Guidance, Accessible Information and Education
- Providing advice and guidance to industry and the public on environmental and radiological protection topics.
- Providing timely and easily accessible environmental information to encourage public participation in environmental decision-making (e.g. My Local Environment, Radon Maps).
- Advising Government on matters relating to radiological safety and emergency response.
- Developing a National Hazardous Waste Management Plan to prevent and manage hazardous waste.

Awareness Raising and Behavioural Change
- Generating greater environmental awareness and influencing positive behavioural change by supporting businesses, communities and householders to become more resource efficient.
- Promoting radon testing in homes and workplaces and encouraging remediation where necessary.

Management and structure of the EPA
The EPA is managed by a full time Board, consisting of a Director General and five Directors. The work is carried out across five Offices:
- Office of Environmental Sustainability
- Office of Environmental Enforcement
- Office of Evidence and Assessment
- Office of Radiation Protection and Environmental Monitoring
- Office of Communications and Corporate Services
The EPA is assisted by an Advisory Committee of twelve members who meet regularly to discuss issues of concern and provide advice to the Board.
EPA RESEARCH PROGRAMME 2014–2020

High-resolution Gridded Datasets of Hydro-climate Indices for Ireland

(2016-W-DS-29)

EPA Research Report

Prepared for the Environmental Protection Agency and Geological Survey of Ireland by

Irish Centre for High-End Computing (ICHEC)

Authors:

Christopher Werner, Paul Nolan and Owen Naughton

ENVIRONMENTAL PROTECTION AGENCY
An Ghniomhaireacht um Chaomhnú Comhshaoil
PO Box 3000, Johnstown Castle, Co. Wexford, Ireland

Telephone: +353 53 916 0600 Fax: +353 53 916 0699
Email: info@epa.ie Website: www.epa.ie
ACKNOWLEDGEMENTS

This report is published as part of the EPA Research Programme 2014–2020. The EPA Research Programme is a Government of Ireland initiative funded by the Department of Communications, Climate Action and Environment. It is administered by the Environmental Protection Agency, which has the statutory function of co-ordinating and promoting environmental research.

The project team would like to thank the project’s co-funders, namely the Environmental Protection Agency and Geological Survey of Ireland, for contributing towards this project. The project team also wish to thank Eoin Whelan, Seamus Walsh and Emily Gleeson of Met Éireann for providing critical datasets for this project, and Raemonn Fealy of Teagasc for providing the Irish Indicative Soil Drainage dataset. The project team thank Alastair McKinstry of the Irish Centre for High-End Computing (ICHEC) for his assistance in uploading the datasets produced in this project to the ICHEC ERDDAP server. The authors would like to acknowledge the members of the project steering committee, namely Keith Lambkin (Met Éireann), Taly Hunter Williams (Geological Survey of Ireland), Conor Quinlan (Environmental Protection Agency), Ian Holman (Cranfield University) and Edward Tully (Irish Water). The research was carried out at ICHEC.

DISCLAIMER

Although every effort has been made to ensure the accuracy of the material contained in this publication, complete accuracy cannot be guaranteed. The Environmental Protection Agency, the authors and the steering committee members do not accept any responsibility whatsoever for loss or damage occasioned, or claimed to have been occasioned, in part or in full, as a consequence of any person acting, or refraining from acting, as a result of a matter contained in this publication. All or part of this publication may be reproduced without further permission, provided the source is acknowledged.

The EPA Research Programme addresses the need for research in Ireland to inform policymakers and other stakeholders on a range of questions in relation to environmental protection. These reports are intended as contributions to the necessary debate on the protection of the environment.
**Project Partners**

**Christopher Werner**  
Irish Centre for High-End Computing  
Trinity Technology and Enterprise Campus  
Grand Canal Quay  
Dublin 2  
Ireland  
Tel.: +353 1 524 1608  
Email: christopher.werner@ichec.ie

**Paul Nolan**  
Irish Centre for High-End Computing  
Trinity Technology and Enterprise Campus  
Grand Canal Quay  
Dublin 2  
Ireland  
Tel.: +353 1 524 1608  
Email: paul.nolan@ichec.ie

**Owen Naughton**  
Department of Built Environment  
Institute of Technology, Carlow  
Carlow  
Ireland  
Email: Owen.Naughton@itcarlow.ie
Contents

Acknowledgements  ii
Disclaimer  ii
Project Partners  iii
List of Figures  vi
List of Tables  ix
Executive Summary  xi
1  Introduction  1
2  Literature Review  2
  2.1 Use of Regional Climate Models for Gridded Data Generation  2
  2.2 Regional Climate Model Data for Ireland  2
  2.3 Hydroclimate Indices  3
  2.4 International Methodologies  9
3  Methodology  11
  3.1 Study Area and Data  11
  3.2 Methods and Bias Corrections  11
4  Results and Validations  14
  4.1 Reference Evapotranspiration  14
  4.2 Actual Evapotranspiration  18
  4.3 Soil Moisture Deficits  27
  4.4 Standardised Precipitation Index  39
  4.5 Agroclimatic Atlas of Ireland  40
5  Conclusions and Recommendations  41
References  42
Abbreviations  48
Appendix 1  List of Archived Variables from Each Model  49
Appendix 2  Agroclimatic Atlas of Ireland  52
Appendix 3  Accessing the Datasets  58
List of Figures

Figure 2.1. WRF domains of 18 km, 6 km and 2 km  
Figure 3.1. Locations of synoptic stations used in hydro-climate model calibration and validation  
Figure 3.2. Raw output and corrected output for annual ET₀ sums at Dublin Airport and Valentia Observatory  
Figure 3.3. Difference in ET₀ yearly sums between corrected and original ET₀ values for Dublin Airport and Valentia Observatory  
Figure 4.1. Scatter plots of daily ET₀ values for each model at Dublin Airport and Valentia Observatory. The colour coding represents deviation from a one-to-one relationship  
Figure 4.2. Annual ET₀ sums for Dublin Airport and Valentia Observatory from 1981 to 2017. The solid black line shows the Met Éireann-calculated values from observations, with a ±10% interval shown by the dashed black line  
Figure 4.3. Average annual ET₀ maps for the COSMO-CLM and WRF (1981–2017) and MÉRA (1981–2016) models. The MÉRA model shows the best fit to observations and the WRF model performs the best of the higher resolution models  
Figure 4.4. Average monthly sums of ET₀ at selected stations for the WRF and COSMO-CLM (1981–2017) and MÉRA (1981–2016) models  
Figure 4.5. Average monthly sums of ET₀ for the WRF and COSMO-CLM (1981–2017) and MÉRA (1981–2016) models  
Figure 4.6. Difference between ET₀ and ETₐ for Dublin Airport for the WRF, COSMO-CLM and MÉRA models (1981–2016)  
Figure 4.7. Scatter plots of daily ETₐ values for well-drained soils for each model at Dublin Airport. The colour coding represents deviation from a one-to-one relationship  
Figure 4.8. Annual ETₐ sums for Dublin Airport and Valentia Observatory synoptic stations from 1981 to 2016. The solid black line shows the Met Éireann-calculated values from observations, with a ±10% interval shown by the dashed black line  
Figure 4.9. Average annual ETₐ maps for well-drained soils for the COSMO-CLM, WRF and MÉRA models (1981–2016)  
Figure 4.10. Average monthly sums of ETₐ for well-drained soils at Dublin Airport and Valentia Observatory for the COSMO-CLM, WRF and MÉRA models (1981–2016)
Figure 4.11. Average monthly sums of ET$_a$ for well-drained soils using the COSMO-CLM, WRF and MÉRA models (1981–2016) 22

Figure 4.12. Average annual ET$_a$ maps for poorly drained soils for the COSMO-CLM, WRF and MÉRA models (1981–2016) 24

Figure 4.13. Average monthly sums of ET$_a$ for poorly drained soils at Dublin Airport and Valentia Observatory stations from 1981 to 2016 24

Figure 4.14. Average monthly sums of ET$_a$ for poorly drained soils using the COSMO-CLM, WRF and MÉRA models (1981–2016) 25

Figure 4.15. Average annual ET$_a$ maps for excessively drained soils for the COSMO-CLM, WRF and MÉRA models (1981–2016) 26

Figure 4.16. Average annual ET$_a$ maps for imperfectly drained soils for the COSMO-CLM, WRF and MÉRA models (1981–2016) 26

Figure 4.17. Average annual ET$_a$ maps incorporating the Teagasc National Soil Map of soil drainage classes for the COSMO-CLM, WRF and MÉRA models (1981–2016) 27

Figure 4.18. Scatter plots of daily SMD values for well-drained soils for Dublin Airport and Valentia Observatory for all models (1981–2016) 28

Figure 4.19. Average annual mean SMD maps for well-drained soils for the COSMO-CLM, WRF and MÉRA models (1981–2016) 29

Figure 4.20. SMD average monthly means for well-drained soils at Dublin Airport and Valentia Observatory (1981–2016) 29

Figure 4.21. Average monthly means of SMD for well-drained soils using the COSMO-CLM, WRF and MÉRA models (1981–2016) 30

Figure 4.22. Average monthly means of SMD for moderately drained soils using the COSMO-CLM, WRF and MÉRA models (1981–2016) 32

Figure 4.23. Average annual mean SMD maps for poorly drained soils for the COSMO-CLM, WRF and MÉRA models (1981–2016) 33

Figure 4.24. Scatter plots of daily SMD values for poorly drained soils at Dublin Airport and Valentia Observatory for all models (1981–2016) 34

Figure 4.25. Average monthly SMD means for poorly drained soils at Dublin Airport and Valentia Observatory (1981–2016) 34

Figure 4.26. Average monthly means of SMD for poorly drained soils using the COSMO-CLM, WRF and MÉRA models (1981–2016) 35

Figure 4.27. Comparison of daily SMDs for (A) well-drained, (B) moderately drained and (C) poorly drained soils for Dublin Airport (1981–2016) 36

Figure 4.28. Average annual mean SMD maps for excessively drained soils for the COSMO-CLM, WRF and MÉRA models (1981–2016) 37
Figure 4.29. Average annual mean SMD maps for imperfectly drained soils for the COSMO-CLM, WRF and MÉRA models (1981–2016) 37

Figure 4.30. Mean monthly SMD incorporating the Teagasc National Soil Map of soil drainage classes using the WRF, COSMO-CLM and MÉRA models (1981–2016) 38

Figure 4.31. Gridded SPI sample for December 2016 for six different timescales 39

Figure 4.32. SPI sample focused on Valentia Observatory for 1 month and 24 months 39

Figure A2.1. Mean daily temperature (left) and mean daily temperature range (right) for 1981–2010 53

Figure A2.2. Mean January minimum temperatures in 1981–2010 (left) and mean July maximum temperatures in 1981–2010 (right) 53

Figure A2.3. Grass-growing season: (a) mean season start date, (b) mean season end date and (c) mean season length in days per year (1981–2010) 53

Figure A2.4. Mean daily temperatures for individual months (1981–2010) 54

Figure A2.5. Average number of frost days per year (1981–2010) 54

Figure A2.6. Mean annual precipitation (mm/year) from Met Éireann gridded observational datasets (1981–2010) 54

Figure A2.7. Mean monthly precipitation (mm/month) from Met Éireann gridded observational datasets (1981–2010) 55

Figure A2.8. Number of wet days at different thresholds: ≥ 1, ≥ 5, ≥ 10, ≥ 15, ≥ 20 and ≥ 30 mm (1981–2010) 55

Figure A2.9. SPI windows from 1981 to 2016 for Belmullet (left) and Cork Airport (right) 56

Figure A2.10. SPI windows from 1981 to 2016 for Casement Aerodrome (left) and Dublin Airport (right) 56

Figure A2.11. SPI windows from 1981 to 2016 for Malin Head (left) and Mullingar (right) 57

Figure A2.12. SPI windows from 1981 to 2016 for Shannon Airport (left) and Valentia Observatory (right) 57

Figure A3.1. Hierarchy of files in ICHEC’s ERDDAP server 58

Figure A3.2. Script using cdo (climate data operators) to obtain the SPI at a user-specified location from the SPI dataset 59
List of Tables

Table 2.1. Overview of soil drainage classes in the HSMD model version 1 from Schulte et al. (2005) 6

Table 4.1. Errors in daily ET₀ values for selected stations from 1981 to 2017 and using an overall weighted average across 22 stations 14

Table 4.2. Errors in yearly summed values of ET₀ at selected stations from 1981 to 2017 using an overall weighted average across 22 stations 16

Table 4.3. RMSEs of monthly summed ET₀ values and daily ET₀ values for each month (1981–2017) using an overall weighted average across 22 stations 18

Table 4.4. Errors in yearly summed values of ETₐ at selected stations and overall weighted averages for 22 stations from 1981 to 2016 20

Table 4.5. Increase in ETₐ (mm/year) for each station for each model (1981–2016) 20

Table 4.6. Errors in yearly summed values of ETₐ for well-drained soils at selected stations from 1981 to 2016 using an overall weighted average across 22 stations 21

Table 4.7. RMSEs of monthly summed ETₐ and daily ETₐ values for each month (1981–2016) using an overall weighted average across 22 stations for well-drained soils 23

Table 4.8. Errors in daily values of ETₐ at selected stations and using overall weighted averages for 22 stations (1981–2016) for poorly drained soils 23

Table 4.9. Errors in yearly summed values of ETₐ at selected stations and using overall weighted averages for 22 stations (1981–2016) for poorly drained soils 24

Table 4.10. RMSEs of monthly summed and daily ETₐ values for poorly drained soil for each month (1981–2016) using an overall weighted average across 22 stations 26

Table 4.11. Errors in daily values of SMDs (mm) (well drained) at selected stations from 1981 to 2016 using an overall weighted average across 22 stations 28

Table 4.12. RMSEs of monthly average SMD (well drained) (mm) and daily values for each month (1981–2016) using an overall weighted average across 22 stations 31

Table 4.13. Errors in daily values of SMD (mm) (moderately drained) at selected stations from 1981 to 2017 using an overall weighted average across 22 stations 31

Table 4.14. RMSEs of monthly average SMD (moderately drained) and daily values for each month (1981–2016) using an overall weighted average across 22 stations 31
Table 4.15. Errors in daily values of SMD (poorly drained) at selected stations from 1981 to 2016 using an overall weighted average across 22 stations 33
Table 4.16 RMSEs of monthly average SMD (poorly drained) and daily values for each month (1981–2016) using an overall weighted average across 22 stations 34
Table A1.1. List of variables from the COSMO-CLM5 dataset produced by ICHEC researchers 49
Table A1.2. List of variables from the WRF dataset (v 3.7.1) produced by ICHEC researchers 50
Table A1.3. List of variables from the MÉRA dataset produced by Met Éireann 50
Table A3.1. List of variables available for download at ICHEC’s ERDDAP server 58
Executive Summary

This report describes the application of numerical weather prediction (NWP) simulations to develop high-quality, long-term, gridded climate datasets of hydro-climate variables for Ireland, covering the period 1981–2016. There is constant demand for such datasets from industry, research and governmental agencies for use in fields such as agriculture, water resource estimation and management, hydrology and hydrogeology, public health, energy and planning and studies on observed climate change trends and vulnerability. Variables such as evapotranspiration and soil moisture conditions are crucial factors in estimating water sustainability, understanding groundwater recharge, agronomic management and the management of flood and drought risk. However, with the exception of temperature and precipitation, spatially and temporally homogeneous, multi-decadal, gridded observational climate datasets are not readily available for hydro-climatic research applications in Ireland.

One approach to generating the requisite gridded datasets is through the use of NWP downscaled simulations. NWP models use mathematical models of the atmosphere to forecast weather based on current weather conditions. NWPs can also be used to "reanalyse" historical weather conditions, whereby past weather observations such as satellite, surface and upper-air conditions are used as model inputs. This report describes the application of downscaled NWP models to produce gridded climate datasets of key hydro-climate variables for Ireland.

In this research the performances of three NWP models (COSMO-CLM, WRF and MÉRA) are compared and analysed to assess their ability to accurately represent hydro-climate variables, focusing on reference evapotranspiration ($ET_0$) as calculated using the Food and Agriculture Organization of the United Nations (FAO) Penman–Monteith equation. Two of the NWP datasets assessed were produced by researchers at the Irish Centre for High-End Computing (ICHEC) using the COSMO-CLM5 and WRF v3.7.1 models. The third dataset (MÉRA) is derived from a 36-year (1981–2016) regional reanalysis of the Irish climate carried out by Met Éireann using the HARMONIE model and the ALADIN-HIRLAM NWP system. The MÉRA simulation included a data assimilation component. All NWP models of the current study downscaled the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-Interim global reanalyses dataset.

Modelled $ET_0$ data are analysed and validated against $ET_0$ data calculated from meteorological observations at 22 Met Éireann synoptic stations across Ireland. Least squared estimator monthly correction factors were applied to all three raw datasets to improve the output. Using these $ET_0$ datasets, actual evapotranspiration ($ET_a$) and soil moisture deficits (SMDs) have been derived using the hybrid soil moisture deficit (HSMD) model, created by Teagasc and in use in Ireland since 2006. The current project employed a more up-to-date model with five drainage classes. The following datasets were derived using MÉRA input variables containing daily, monthly, seasonal and yearly time steps:

- $ET_0$
- $ET_a$ (five drainage classes);
- SMDs (five drainage classes).

The datasets described above are also available for the COSMO-CLM and WRF models with 1.5-km and 2-km grid spacing, respectively. Additionally, the Teagasc Indicative Soil Drainage Map has been implemented to capture the actual soil conditions throughout the country. All datasets are available for download through the ICHEC ERDDAP server, which can be found at https://erddap.ichec.ie/erddap/files/EPA_Hydroclimate.

Across all three models, the MÉRA model is the best performer for $ET_0$. Using a weighted average across 22 synoptic stations, root mean square errors equated to 0.337 mm/day for the MÉRA model compared with 0.402 mm/day and 0.442 mm/day for the WRF and COSMO-CLM models, respectively. The MÉRA model also performs best for the $ET_a$ and SMD variables and therefore the MÉRA datasets are the recommended datasets to be used as indicative maps for Ireland.
An additional project output was to facilitate an update to the Agroclimatic Atlas for Ireland. Met Éireann high-resolution (1-km) daily gridded datasets of temperature and precipitation were used to derive agro-climate variables such as the Standardised Precipitation Index (SPI) and growing season. Gridded datasets of the SPI for intervals of 1, 2, 3, 6, 12, 24 and 48 months have been derived for 1981–2016 using both the observational datasets and the NWP models specified above.
1 Introduction

There is constant demand from industry and research and governmental agencies for high-quality, long-term, gridded datasets with high spatial and temporal resolution for conducting climate research. These data have the potential to be used in a wide variety of fields such as agriculture (Collins and Cummins, 1996; Perry and Hollis, 2005; Olesen et al., 2007; Abatzoglou, 2013; Jones and Thornton, 2013), hydrology and hydrogeology (Hay et al., 2002; Analitis et al., 2008; Rajeevan and Bhat, 2009; Keshta and Elshorbagy, 2011; Di Luca et al., 2012; Duethmann et al., 2013; Williams et al., 2013; Merz et al., 2014; Schamm et al., 2014; Seyyedi et al., 2014), public health (Kunkel et al., 1999; D’Ippoliti et al., 2010; Vautard et al., 2013), energy (Troen and Petersen, 1989; SEAI, 2016; Gallagher et al., 2014; Gallagher et al., 2016; Slater, 2016) and planning (Holman et al., 2005; Bouwer, 2011) and in studies on observed climate change trends and vulnerability (IPCC, 2014; Bollmeyer, 2015). The need for spatially represented hydro-climate variables is a prerequisite for many aspects of hydrological and ecological assessment. Variables such as evapotranspiration and soil moisture conditions are crucial factors in estimating water sustainability, understanding groundwater recharge, agronomic management and the management of flood and drought risk. However, at present gridded observational climate datasets are not readily available in Ireland, except for temperature and precipitation (Walsh, 2012).

In order to characterise groundwater and surface water systems, and to facilitate climate adaptation, a greater understanding of the primary processes driving energy and water exchanges within the hydrological cycle is required. It is therefore necessary to provide the evidence needed to inform policymakers, planners and stakeholders of potential climate change-related issues in Ireland. Such studies also support the development of pre-emptive mitigation strategies necessary to contribute towards developing a climate-resilient Ireland. To fully comprehend future climate change, a thorough analysis of the observational past is required.

As mentioned above, the only readily available gridded climate datasets available in Ireland are those for precipitation and temperature (Bollmeyer et al., 2015) and these variables alone are insufficient to enable scientists and policymakers across all sectors to make well-informed decisions. The lack of up-to-date gridded hydrological datasets, particularly for evapotranspiration, represents a serious information gap in Irish meteorology and agro-climate studies.

This gap was outlined in the 2012 Catchment Flood Risk Assessment and Management (CFRAM) National Preliminary Flood Risk Assessment (PFRA) (CFRAM, 2012), which stated that “the information required to undertake a predictive analysis of the potential flood risk impacts of climate change is not currently available, but is under development and once available will be used to review the PFRA outcomes”. The gap was also highlighted in the context of groundwater recharge assessment and the Water Framework Directive quantitative status characterisation (Williams et al., 2013). The datasets produced as part of the current project will allow scientists, engineers and policymakers to study observed changes and patterns in hydrological/hydrogeological datasets to an extent not covered before in Ireland and mitigate against the projected adverse effects in the coming decades. The performances of (1) the COSMO-CLM5 model, developed by Consortium for Small-scale Modelling and Climate Limited-area Modelling Community, (2) the Weather Research and Forecasting (WRF) model and (3) the Met Éireann Re-Analysis (MÉRA) datasets are compared and analysed to assess their ability to accurately represent hydro-climate variables. The overall goal of this project was to produce definitive gridded datasets of hydro-climate variables including reference (ET₀) and actual (ETₐ) evapotranspiration, soil moisture deficits (SMDs), rainfall intensity and the Standardised Precipitation Index (SPI) for the period 1981–2016 for use by industry, policymakers, the general public and researchers.
2 Literature Review

2.1 Use of Regional Climate Models for Gridded Data Generation

One approach to generating homogeneous, long-term gridded datasets is using numerical weather prediction (NWP) hindcast simulations. NWP models use mathematical models of the atmosphere to forecast weather based on current weather conditions. NWP can also be used to reanalyse historical weather conditions, whereby past weather observations such as satellite, surface and upper-air conditions are used as model inputs. Using data assimilation methods, a complete estimate of the atmospheric state is computed that is both dynamically consistent and close to observations. The primary advantage of using reanalysis data is that they provide the best estimate of the four-dimensional atmospheric state, for both observed variables and essential climate variables, which are not often measured (Dee et al., 2014; Bollmeyer et al., 2015). Such examples of global reanalysis datasets include ERA-Interim (Dee et al., 2011) from the European Centre for Medium-Range Weather Forecasts (ECMWF) and the National Center for Atmospheric Research (NCEP) Climate Forecasting Systems Reanalysis. However, these global reanalysis datasets have resolutions of the order of 80 km, which is too coarse to be of use in regional studies.

To address this problem, a regional climate NWP model (RCM) is typically employed to dynamically downscale the coarse global reanalysis datasets at a higher resolution over the area of interest. This downscaling can also include the assimilation of local observations, known as a regional reanalysis. If these local observations are not available a more general RCM approach is implemented. The constraints imposed by local observations should yield a more accurate analysis than the general RCM approach, which lacks these local observations. However, the data assimilation systems of the NWP model do not exactly follow observations because of a broader constraint requiring physical and dynamical consistency over the three-dimensional volume of the atmosphere. Both approaches have value, particularly when multiple NWP models are employed.

The overall basis of the RCM method is to dynamically downscale the coarse information provided by the global reanalysis data and provide high-resolution information on a sub-domain of interest. All models from global down to regional scale have errors, however, and more errors are introduced from the boundaries of the regional models. Numerous studies have demonstrated that high-resolution RCMs improve the simulation of precipitation (Rajeevan and Bhate, 2009; Saha et al., 2010; Di Luca et al., 2012; Lucas-Picher et al., 2012; Duethmann et al., 2013; Kendon et al., 2012; Kendon et al., 2014; Bieniek et al., 2016; McGrath and Nolan, 2016) and topography-influenced phenomena and extremes with relatively small spatial or short temporal character (Feser et al., 2011; Feser and Barcikowska, 2012; Shkol’nik et al., 2012; Flato et al., 2013). An additional advantage is that the physically based RCMs explicitly resolve more small-scale atmospheric features and provide a better representation of convective precipitation (Rauscher et al., 2010) and extreme precipitation (Kanada et al., 2008). Other examples of the added value of RCMs include improved simulation of near-surface temperature (Feser, 2006; Di Luca et al., 2016). The latest Intergovernmental Panel on Climate Change (IPCC) report has concluded that there is “high confidence that downscaling adds value to the simulation of spatial climate detail in regions with highly variable topography and for mesoscale phenomena and extremes” (Stocker et al., 2013).

2.2 Regional Climate Model Data for Ireland

Researchers at the Irish Centre for High-End Computing (ICHEC) completed two high-resolution historical simulations of the Irish climate, by downscaling ERA-Interim data for the period 1980 to present using the COSMO-CLM5 (Rockel et al., 2008) and WRF v3.7.1 (Skamarock et al., 2008) RCMs, with maximum spatial resolutions of 1.5 km and 2 km, respectively. The WRF nested model domains have 18-km, 6-km and 2-km grid spacings and are shown in Figure 2.1. The COSMO-CLM domains have the same resolution apart from the innermost domain (1.5 km)
and are slightly larger than the corresponding WRF domains.

In 2017, Met Éireann completed a 36-year (1981–2016) regional reanalysis of the Irish climate using the HARMONIE model and the ALADIN-HIRLAM NWP system, called MÉRA (Whelan et al., 2016; Gleeson et al., 2017). In contrast to the COSMO-CLM and WRF simulations, MÉRA includes data assimilation, utilising time series of surface observations (Whelan et al., 2015), and has a different projection. MÉRA has performed with high accuracy, with small biases in temperatures, pressure and 10-m wind speeds, and outperformed “ERA-Interim reanalysis particularly in terms of standard deviations in screen-level temperatures and surface winds” (Gleeson et al., 2017) and compares well with surface observations. Because of the data assimilation component, the MÉRA model exhibits better skill than the WRF and COSMO-CLM models despite the lower resolution. However, the WRF and COSMO-CLM models add value given their finer spatial resolutions. The comparison of these different models provides information on the relative skill of the RCM methodologies.

In the current study, the COSMO-CLM, WRF and MÉRA datasets are compared and analysed to assess their ability to accurately represent hydro-climate variables. The overall goal of this project was to produce definitive gridded climate datasets of hydro-climate variables such as ET₀ and ETₐ, SMDs, rainfall intensity and the SPI for the period 1981–2016 for use by industry, policymakers, the general public and researchers. Data for 2017 are made available for COSMO-CLM and WRF.

2.3 Hydroclimate Indices

2.3.1 ET₀

Evapotranspiration is the transfer of water from the land to the atmosphere through a combination of two separate processes, evaporation from the land surface and transpiration from vegetation. Although evapotranspiration can be measured directly, meteorological agencies generally use calculation methods to determine a “reference” evapotranspiration (ET₀), which is evapotranspiration from a reference surface that is not water limited. The reference crop is typically taken as grass with an assumed height of 0.12 m, a fixed surface resistance of 70 s/m and an albedo of 0.23 (Allen et al., 1998). The potential evapotranspiration of any crop can be calculated by multiplying this value by a crop coefficient, Kc, which depends on the crop type and time of growth.

There have been many developments and improvements in the calculation of evapotranspiration over time as it plays an important role in the field of agro- and hydro-meteorology. It is a crucial factor in estimating water sustainability and understanding agronomic management, is of more importance in a changing climate and is important in the management of flood and drought risk. Numerous methods of calculating evapotranspiration exist, including pan-based coefficient methods, such as described in Allen et al. (1998), and the Pereira models (Pereira et al., 1995). These methods will not be considered for this study, as ET₀ in Ireland is typically calculated from observed meteorological data recorded at synoptic stations.

There are numerous approaches for estimating ET₀, based on empirical, mass transfer, temperature, radiation and combination and direct measurement methods (Blaney and Criddle, 1950; Makkink, 1957; WMO, 1966; Mahringer, 1970; Priestley and Taylor, 1972; Szász, 1973; Doorenbos and Pruitt, 1977; Burman and Pochop, 1994). Direct measurements of ET₀ are severely limited in Ireland and so these were not considered in this study; they are recommended
more over monthly or longer time periods. Prior to 2006, Met Éireann employed the radiation-based Makkink methodology for estimating $ET_0$ (Keith Lambkin, Met Éireann, 2017, personal communication; https://www.met.ie/climate/services). Subsequently, the combination method of the Food and Agriculture Organization of the United Nations (FAO) Penman–Monteith equation has been used for $ET_0$ estimation. The Penman-Monteith method is recommended by the World Meteorological Organization as the sole standard method for estimating $ET_0$, as it has been shown to have a strong likelihood of correctly predicting $ET_0$ in a wide range of locations and climates. Studies such as that by Rácz et al. (2013), which compared 10 different $ET_0$ methodologies, found that the Penman–Monteith equation provided the best estimates.

Penman (1948) developed a method of calculating $ET_0$ by combining the energy balance with the mass transfer method and derived the equation to compute open source evaporation from standard climatological records of sunshine, temperature, humidity and wind speed. The method has been further developed, resulting in the Penman–Monteith $ET_0$ formula, given as:

$$ET_0 = \frac{0.408 \Delta (R_n - G) + \gamma \left( \frac{900}{T_w + 273} \right) u_s (e_s - e_a)}{\Delta + \gamma (1 + 0.34 u_s)}$$

(2.1)

where $ET_0$ is the measure in mm/day, $R_n$ is the net surface radiation (MJ/m²/day), $G$ is the soil heat flux (MJ/m²/day), $T_w$ is the mean daily 2-m temperature (°C), $u_s$ is the mean daily 2-m wind speed (m/s), $e_s$ is the daily saturation vapour pressure (kPa), $e_a$ is the daily actual vapour pressure (kPa), $\Delta$ is the slope of the vapour pressure curve (kPa/°C) and $\gamma$ is the psychrometric constant (kPa/°C).

In line with international best practice and current practices at Met Éireann, the FAO Penman–Monteith equation has been used for calculating $ET_0$ in this study.

Other notable methodologies for estimating $ET_0$, including the Thornthwaite (1948), Hargreaves and Samani (1985) and Penman (1948) methods, can be used in place of the Penman–Monteith equation when all required input variables are not available (Hargreaves and Allen, 2003; Chen et al., 2005). Methods such as these have significant advantages over the Penman–Monteith equation when data are limited as they require fewer input parameters and are relatively easy to calculate. The quantity of input variables in the Penman–Monteith equation has its issues as many locations worldwide do not record all of the required meteorological variables. Appropriate documentation is available (Allen et al., 1998) for when this occurs.

Following the estimation of evapotranspiration for the grass reference crop outlined in Allen et al. (1998) and Zotarelli et al. (2010), to obtain evapotranspiration for a certain crop, a crop coefficient, $K_c$, must be applied:

$$ET_c = K_c \cdot ET_0$$

(2.2)

where $ET_c$ is the evapotranspiration from disease-free, well-fertilised crops, grown in large fields under optimum soil water conditions and achieving full production under the given climatic conditions. Depending on the crop and time of year, different $K_c$ values are applied, and are typically employed for areas where irrigation is a prominent activity. A full list of the different $K_c$ values is outlined in Chapter 6 in Allen et al. (1998).

### 2.3.2 $ET_0$ and SMDs

The calculation of $ET_0$ is determined by the available energy supply and is based on the assumption that the system is not water limited, i.e. an ample supply of water is available. However, the actual rate of water loss from a vegetated surface does not always proceed at the potential rate $ET_0$. When vegetation is unable to extract water from the soil column, $ET_0$ falls below the potential rate $ET_0$. This difference between potential and actual rates is dependent on the soil moisture content.

When a soil is saturated it will not hold any more water, and any further rainfall is drained via run-off or percolation to groundwater. When rainfall ceases, the soil becomes unsaturated until it reaches “field capacity”, the water that the soil can hold against the force of gravity. When the soil moisture is at or above field capacity, evapotranspiration can occur at the potential rate ($ET_p = ET_0$). In the absence of further rainfall, soil moisture gradually becomes depleted to produce a SMD, defined as the amount of water required to restore the soil to field capacity. As the SMD increases, water becomes more difficult for vegetation to access and $ET_0$ becomes progressively less than $ET_0$. 

High-resolution Gridded Datasets of Hydro-climate Indices for Ireland
Actual evapotranspiration is of particular interest to agriculturalists and hydrologists for groundwater research for the purposes of monitoring decreases in crop productivity and producing groundwater recharge maps, respectively (Burke, 1962; Brereton and Keane, 1982; Williams et al., 2013). In Ireland, ETa and SMD are typically not directly measured but are instead estimated from measurements of ET0 and precipitation. In a broadly similar climate to Ireland, the UK Meteorological Office has established a regular procedure for evaluating agricultural water shortage in Britain using the water budget approach. The UK’s Meteorological Office Rainfall and Evaporation Calculation System (MORECS; Thompson et al., 1981) (discussed further in section 2.4.) is applied to grid cells of size 40 × 40 km and employs regularly collected meteorological data to estimate ETa using a modified Penman equation that accounts for both meteorological conditions and vegetation characteristics.

Several studies have used remote sensing (RS) to estimate ETa rather than physical observations (Soer, 1980; Carlson et al., 1995; Timmermans and Meijerink, 1999; Wu et al., 2006; Senay et al., 2007; Gao et al., 2008; Teixeira, 2010; Elhag et al., 2011; Glenn et al., 2011a,b). There are some advantages to this as ETa can be determined on a large scale rather than by point measurement analysis. However, each captured image is still a snapshot and the temporal resolutions can vary between satellites. Field data are usually required in interpreting and calibrating RS imagery, and validating models for large areas, but extensive fieldwork in such cases is not necessarily required (Kite and Droogers, 2000). RS is mostly prominent in areas where irrigation is a key activity.

No single method of measuring or calculating evapotranspiration is without fault as some point analysis methods are difficult to apply spatially (Wu et al., 2006), and traditionally ETa has been computed as a residual in water balance equations. Estimates of ET0 are derived by means of a ratio or indirectly from field measurements at meteorological stations (Kite and Droogers, 2000).

In Ireland, ETa and SMD are not widely monitored directly (Mills, 2000) but are instead calculated using the hybrid soil moisture deficit (HSMD) model implemented by Met Éireann in 2006 (Schulte et al., 2005; Keith Lambkin, Met Éireann, 2017, personal communication; https://www.met.ie/climate/services), with a newer version described in Schulte et al. (2015). In this model ETa is assumed to reduce linearly to zero as SMD approaches a theoretical maximum value, beyond which ETa is assumed to be zero. In the Met Éireann model ETa is given by:

\[
ET_a = ET_0 \frac{SMD_{max} - SMD_{c}}{SMD_{max} - SMD_c} \tag{2.3}
\]

where SMDmax is a theoretical maximum SMD value, SMDc is the SMD at time t–1 and SMDc is a critical value above which moisture availability is no longer a limiting factor (Aslyng, 1965). When SMD is less than SMDc moisture is not limiting respiration and is assumed to equal ETa. For SMD values below this critical level, it is assumed that ETa decreases linearly to zero as the SMD approaches the critical maximum value.

Soil moisture conditions are an important interface between agriculture and the environment because of their impact on the length of the grazing season, grass growth conditions and nutrient uptake. The balance exchange is driven by the hydrological cycle, one of the most fundamental cycles in the earth–atmosphere system. The hydrological cycle refers to the passage of water in gaseous, liquid and solid forms between the oceans, atmosphere, lithosphere and biosphere. It can easily be expressed as a water budget, accounting for precipitation (P), evapotranspiration (E), run-off (R) and the fluctuations in the water stored in the soil (DS) as:

\[
P - E - R = \Delta S \tag{2.4}
\]

The difference between evapotranspiration and precipitation represents differences in water stored within the soil. For a saturated soil, run-off will be generated, and the saturation of the soil is often represented by the “field capacity”, the depth of water that can be held in the soil against the force of gravity. When a soil is at field capacity, any excess water runs off overland or percolates downwards through the soil. Measures for countrywide SMDs and soil moisture content are not common; however, the European Space Agency (ESA) has been monitoring global soil moisture using active and passive microwave instruments (Silvestrin et al., 2001; Mecklenburg et al., 2012). A number of studies have also derived soil moisture datasets from radar and satellite imagery (Ulaby, 1974; Huisman et al., 2003; Wagner et al., 2007). A number of international studies have
attempted to estimate SMDs using meteorological models (Lockwood et al., 1989). In Ireland, attempts have been made to evaluate the soil moisture and deficit in the context of the water budget and soil associations (Gardiner and Radford, 1980). Some of the most notable attempts involved the implementation of a $5 \times 5$ km grid superimposed onto Ireland using measured meteorological variables (precipitation, temperature, sunshine hours) to calculate each of the water budget terms (Mills, 2000) and to calculate $ET_0$ and SMDs for North County Dublin from 1950 to 1981 using the Penman method (Burke, 1962). However, with recent advances in climate modelling and observations, this can be improved on.

In Ireland, a method for estimating SMDs across the whole country, the HSMD model (Schulte et al., 2005), was derived by Teagasc, which has been used at Met Éireann since 2006. The preliminary calculations are described as:

$$SMD_t = SMD_{t-1} - Rain + ET_a + Drain$$ (2.5)

where $SMD_t$ and $SMD_{t-1}$ are the SMDs on day $t$ and day $t-1$ respectively, $Rain$ is the daily incoming precipitation, $ET_a$ is the daily $ET_a$ and $Drain$ is the amount of water drained daily by percolation and/or overland flow, which is dependent on the soil drainage capacity. There are three soil drainage classes, outlined in Table 2.1. As with the water budget equation, SMDs and surpluses are computed from differences between rainfall, $ET_a$ and drainage, with soil moisture surpluses assumed to be removed by drainage and surface run-off over time.

Since the implementation of this model, an updated and higher resolution version has been developed, the HSMD model version 2 (Hallett et al., 2014; Schulte et al., 2015). The new model includes two new soil drainage classes as well as an optional module to account for the topographic wetness index. The two new drainage classes included are “excessive” and “imperfect”. The new classes follow the same characteristics as for the older corresponding classes, with the exception of the excessive class, for which the $SMD_{\text{max}}$ value is 50 mm. The imperfect class has a drainage of 3 mm, with other characteristics similar to those for the moderately and poorly drained classes. The topographic wetness index is used in locations that receive water from both direct precipitation and adjacent areas via overland flow. The only difference in the equations is the topographic wetness index, from which a $Y$ modifier is derived and put as a denominator to the drain term.

Other methods of calculating SMDs include methods from the FAO (Allen et al., 1998) and the Penman–Grindley model (Grindley, 1969). These models calculate $ET_a$ using alternative methods to represent the crop stress factor. For the standard Penman–Grindley approach, the potential evapotranspiration term (taken to be the same as $ET_0$) is reduced once the SMD reaches a so-called rooting constant, the value below which evapotranspiration may occur at its maximum rate. When this occurs, $ET_a$ is instantly reduced to 10% of potential evapotranspiration, during a period in which the crop is stressed. During this time, the SMD is less than the crop rooting constant, beyond which transpiration reduces. The point beyond which transpiration ceases is known as the wilting point. The FAO assumes that $ET_a$ decreases linearly from the rooting constant to the wilting point. The difference from the Schulte model is the inclusion of the rooting constant and wilting points. For practical reasons, the updated Schulte model will be implemented in this study. The primary reasoning is the inclusion of different soil drainage characteristics, which the Penman–Grindley model does not implement. Second, the Penman–Grindley method uses the Penman $ET_0$ method as an input instead of the Penman–Monteith method.

Table 2.1. Overview of soil drainage classes in the HSMD model version 1 from Schulte et al. (2005)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Well drained</th>
<th>Moderately drained</th>
<th>Poorly drained</th>
</tr>
</thead>
<tbody>
<tr>
<td>SMD$_{\text{max}}$</td>
<td>110 mm</td>
<td>110 mm</td>
<td>110 mm</td>
</tr>
<tr>
<td>SMD$_{\text{min}}$</td>
<td>0 mm</td>
<td>–10 mm</td>
<td>–10 mm</td>
</tr>
<tr>
<td>Drainage</td>
<td>–</td>
<td>10 mm/day</td>
<td>0.5 mm/day</td>
</tr>
<tr>
<td>Comments</td>
<td>Soil never saturates, remaining at field capacity even on very wet winter days</td>
<td>Soil may saturate on wet winter days, but returns to field capacity on first dry day</td>
<td>Soil saturates on wet winter days, with water surplus drained at very slow rates</td>
</tr>
</tbody>
</table>
method, which is used by Met Éireann for calculating ET₀. Finally, the Penman–Grindley method is believed to not operate satisfactorily when the surface or the subsurface run-off is a significant part of the soil water balance (Mackenzie et al., 1991).

Soil moisture deficits are an effective way of monitoring the soil conditions and a measure of the difference between water in the soil and the amount that the soil can actually hold. As mentioned previously, this is known as the field capacity of the soil and can be considered as one of the most viable options for ascertaining soil moisture conditions. One study has gone further to develop a SMD index and evapotranspiration deficit index for agricultural drought monitoring, based on weekly values (Narasimhan and Srinivasan, 2005). They work in a similar way to the SPI (McKee et al., 1993) and represent conditions from extremely dry to extremely wet. The study by Narasimhan and Srinivasan (2005) includes the acknowledgement that the drought indices introduced needed to be aggregated at spatial and temporal scales for comparison with other drought indices.

Droughts are rare in Ireland; however, the drought during the summer months of 2018 makes this a more viable option as the impacts of climate change become more apparent in Ireland. The applications of the SPI are further discussed in the following section.

2.3.3 Precipitation

Rainfall intensities

Rainfall intensities are used primarily in run-off analysis and are of huge importance in agricultural and groundwater monitoring (Allen et al., 1998; Williams et al., 2013). When rain falls, the first drops of water are intercepted by the leaves and stems of the vegetation, usually referred to as the “interception storage”. As the rain continues, water reaching the ground surface infiltrates into the soil until it reaches a stage where the rate of rainfall (the intensity) exceeds the infiltration capacity of the soil. After this time, surface ponding occurs and depression areas are filled, after which run-off is generated. The infiltration capacity of the soil is dependent on its structure and texture, as well as the soil moisture content as a result of previous rainfall or dry periods. The main factors that affect run-off are soil type, vegetation cover, the slope and the catchment size. The details of these factors are outside the scope of this project and are more applicable to end users of rainfall intensity datasets.

Additionally, rainfall intensities have been utilised in intensity–duration–frequency curves (Linsley, 1958; Jalee and Farawn, 2014; Liew et al., 2014), which are common tools used by insurance industries and in water resources engineering for the planning, design and operation of water resources projects. These curves typically go down to timescales of 15 minutes or less, which goes beyond the scope of the datasets being produced, which have a maximum temporal resolution of 1 hour.

Standardised Precipitation Index

The SPI has been accepted as the best practice standard for monitoring drought events since its inception in 1993 (McKee et al., 1993) and it has replaced the Palmer Drought Severity Index (PDSI) (Palmer, 1965; WAMIS, 2012). The SPI allows an analyst to determine the rarity of a drought at a given timescale of interest for any rainfall station with long-term historical datasets. The SPI is typically used over timescales ranging from months to years but can be updated daily to provide a moving window approach. Timescales of less than 3 months can be used to assess drought severity.

Advantages of the SPI include its simplicity, its being based solely on rainfall, its ability to describe drought at different timescales and its comparability across different climatic regimes, and its probabilistic nature provides a historical context that is well suited for decision making (Bussay et al., 1999). Its simplicity is also a disadvantage, as calculation is based solely on precipitation; there is no soil–water balance component and no ability to calculate evapotranspiration ratios. An updated version, developed in 2010 (Vicente-Serrano et al., 2010), attempts to address this latter issue of evapotranspiration and will be covered later in this section. Studies of the SPI’s usage have been carried out in Hungary (Edwards, 1997; Szalai and Szinell, 2000) and Greece (Karavatis et al., 2011), with streamflow best described with 2- to 6-month timescales. At 5–24 months there were good relationships to groundwater levels and agricultural drought was well represented at scales of 2–3 months in the Hungary examples. In Greece, where drought is becoming more of a concern, the SPI described drought conditions very well, establishing the onset,
ending and severity levels of exceptional drought events.

Mathematically, the SPI is based on the cumulative probability of a given rainfall event occurring at a location. The historical rainfall data are fitted to a gamma distribution, through a process of maximum likelihood estimation of the gamma distribution parameters $\alpha$ and $\beta$. The probability density function is defined as:

$$ g(x) = \frac{1}{\beta^{\alpha} \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} $$  \hspace{1cm} (2.6)$$

where $\alpha$ and $\beta$ are shape and scale parameters, respectively, and $x$ is the amount of precipitation. The gamma function $\Gamma(\alpha)$ is defined as:

$$ \Gamma(\alpha) = \lim_{n \to \infty} \sum_{v=0}^{n-1} \frac{n!}{y + v} \int_{0}^{y} e^{-t} dt $$  \hspace{1cm} (2.7)$$

Simplified approximations for the $\alpha$ and $\beta$ parameters are given by:

$$ \alpha = \frac{1}{4A} \left(1 + \sqrt{1 + \frac{4A}{3}}\right) $$  \hspace{1cm} (2.8)$$

$$ \beta = \frac{\bar{x}}{\alpha} $$  \hspace{1cm} (2.9)$$

where:

$$ A = \ln(n) \left(\frac{\sum \ln(x)}{n}\right) $$  \hspace{1cm} (2.10)$$

and $n$ is the number of observations (Lana et al., 2001). There are a number of other approximations to calculate these parameters, which depend on practicality and size of dataset.

The SPI is measured on a scale of $-3$ to $+3$, with zero representing normal conditions, values less than $-2$ representing severe drought and values greater than $+2$ representing severe wet conditions.

Despite SPI being typically used as a drought index, recent studies have demonstrated its use in flood risk management. One such study focused on recurrent floods in the southern Cordoba Province in Argentina (Seiler et al., 2002). The results showed that the SPI was able to satisfactorily explain the development of conditions leading up to three major flood events in the region from 1979 to 1998. The results indicated the potential for SPI as a tool for monitoring hydrological conditions and flood risk and the potential of incorporating SPI analysis into a regional system for climate risk monitoring as part of a comprehensive flood mitigation programme.

The different time periods over which the SPI is calculated enhances the analysis capacity, as it allows the estimation of different antecedent conditions in the soils. Shorter scales of 3–6 months quantify superficial soil water, which bears significance for agriculture. In contrast, longer accumulation scales indicate the state of subsurface moisture, as well as other surface and subsurface water resources.

The lack of consideration in the SPI of other variables such as evapotranspiration was addressed by Vicente-Serrano et al. (2010), with the Standardised Precipitation Evapotranspiration Index (SPEI). The SPEI is based on both precipitation and temperature data and has the advantage of combining multi-scalar character with the capacity to include the effects of temperature variability on drought assessment. The SPEI differs from the SPI as it includes a climatic water balance, the accumulation of water deficit and surpluses at different timescales and the adjustment to a log-log logistic probability distribution. The SPEI performed well under global warming conditions and identified an increase in drought severity associated with higher water demand as a result of evapotranspiration. The SPEI study (Vicente-Serrano et al., 2010) used the Thornthwaite (1948) method of calculating evapotranspiration because of its simplicity, which is given as:

$$ ET = 16 \left(\frac{N}{12}\right) \left(\frac{NDM}{30}\right) \left(\frac{10T}{I}\right)^{m} $$  \hspace{1cm} (2.11)$$

where $T$ is the monthly mean temperature in °C; $m$ is a cubic equation coefficient based on the value $I$ (see Vicente-Serrano et al., 2010); $NDM$ is the number of days in a month; $N$ is the maximum number of sun hours calculated from the hourly angle of sun rising, the latitude and solar declination; and $I$ is a heat index. This heat index is calculated as the sum of 12 monthly index values, $i$, which is derived from:

$$ i = \left(\frac{T}{5}\right)^{1.54} $$  \hspace{1cm} (2.12)$$

Both the SPI and the SPEI have great potential for application in Ireland, for example in the analysis of droughts and winter floods. These indexes have not been applied in Ireland or many places worldwide and can be used to establish Ireland’s place in a warming world.
2.4 International Methodologies

As evapotranspiration and soil moisture contents are critical hydroclimate variables, many nations have derived methodologies for spatially observing and modelling these variables. This section will focus on relevant methodologies, which include systems implemented in the UK, USA, Australia and New Zealand.

2.4.1 UK

The UK Meteorological Office Rainfall and Evaporation Calculation System was implemented in the UK in 1978 as a replacement for the estimated soil moisture deficit (ESMD) and was updated in 1995 (Hough and Jones, 1997). Compared with methods currently in use in Ireland, the availability of digitalized soil databases across the UK allowed MORECS access to the soil data for calculations of actual soil moisture rather than soil drainage type. This highlights the need for actual soil moisture measurements across the different soil types in Ireland. MORECS is produced in a grid square format of 40 × 40 km and uses daily synoptic weather data to provide estimates of weekly and monthly evaporation and SMD in the form of averages. The potential evapotranspiration is calculated for each grid square for a range of surface covers from bare soil to forest, using a modified form of the Penman–Monteith equation (Monteith and Unsworth, 1990). Estimates of potential evapotranspiration are converted to estimates of ETa by progressively reducing the rate of water loss from the potential value to zero as the available water decreases from a fraction of its maximum value to zero.

Crop models are also used in MORECS, but it should be noted that they are idealised representations of crop growth. The models describe aspects such as plant development through the growth stages, the leaf area index, crop height, variation of crop canopy resistance with weather and crop age. The water in the soil available for plant growth has been the subject of wide-ranging research over the last 40+ years in the UK. Difficulties arise in estimating the amount of water available for plant growth because of variables such as rooting depths and in simulating the process by which roots extract water from the soil. MORECS is based on suctions (measured in kPa); the lower limit of ≈5 kPa approximates to field capacity and the higher value of ≈1500 kPa indicates the wilting point. The system outlines two classes of water availability based on these values. For values between 5 and 200 kPa, the retention is termed “easily available water” (EAW). For suctions between 200 and 1500 kPa, it is termed “restricted available water” (RAW). The summation of these two terms provides the total available water (TAW) or available water capacity.

Soil available water data are extracted from the Land Information System, which contains unique soil and related environmental data for England and Wales, the UK’s National Soil Map and a National Catalogue of Soils that cover a wide range of properties from water retention to density measurements (Ragg and Proctor, 1983; Hallett et al., 1996). The data are taken from large samples and have an overall resolution of 100 m × 100 m and overall available water content (AWC) values for grid squares of 1 km × 1 km. Systems such as MORECS show the complicated overall structure of an evapotranspiration and soil moisture network required to yield a more sophisticated network.

Other UK datasets are CHESS (Climate, Hydrological and Ecological research Support System), JULES (Joint UK Land Environment Simulator) and COSMO-UK. The first of these draws mainly on MORECS data (temperature, humidity, wind speeds, sunshine hours) downscaled to 1-km resolution. The CHESS datasets can be used with rainfall datasets to drive the JULES model, a land surface model that includes soil moisture, soil temperature and evaporation. Finally, the COSMOS-UK dataset is a network of soil monitoring stations for the UK that provides near-real-time soil moisture data for use in a variety of applications including farming, water resources, flood forecasting and land surface modelling. Networks and datasets such as these, which have real-time applications, should be seen as a matter of high importance for Ireland in the near future.

2.4.2 USA

In the USA, the evapotranspiration network is estimated using a regression with climate and land cover data (Sanford and Selnick, 2013). Precipitation and streamflow records were compiled for 838 watersheds for the period 1971–2000 to obtain long-term estimates of ETa. Precipitation and temperatures were used from the PRISM datasets and land cover from the US Geological Survey
High-resolution Gridded Datasets of Hydro-climate Indices for Ireland

(USGS) National Land Cover Dataset. The system has been developed since its inception and at present ArcGIS actual evapotranspiration layers are available at 1-km cell size, derived from the MOD16 Global Evapotranspiration Product and MODIS satellite imagery. However, despite using the Penman–Monteith equation, the methodology uses satellite RS data rather than physical observations and at present the data cover only the period 2000–2010 (Mu et al., 2013). Additionally, the USGS has evapotranspiration networks on a state-by-state basis rather than across the whole country. Soil moisture estimates in the USA are surprisingly limited at present but new measures are being put in place to monitor droughts. Puerto Rico obtains excellent evapotranspiration and countrywide soil moisture monitoring from the GOES-PRWEB satellite, which provides near-real-time maps of ET0, ETa, soil moisture content and radiation (PRAGWATER).

2.4.3 New Zealand

In New Zealand, the National Institute of Water and Atmospheric Research (NIWA) employs a virtual climate station network that produces daily datasets based on the spatial interpolation of actual data observations made at climate stations across the country. These observations include rainfall, potential evapotranspiration and soil moisture and are interpolated using a spline model (Tait et al., 2006; Tait and Woods, 2007). In addition to evapotranspiration, SMDs, soil moisture anomalies and the SPI over 30- and 60-day timescales are updated daily, with comparisons made from averages and the previous year. The evapotranspiration values in New Zealand are calculated using the Penman method (Penman, 1963; Westerhoff, 2015).

2.4.4 Australia

In Australia, the Bureau of Meteorology and the Cooperative Research Centre for Catchment Hydrology released a set of evapotranspiration maps for Australia in 2001 as part of the Bureau’s Climatic Atlas series (Australia Bureau of Meteorology and Wang, 2001; Chiew et al., 2002). These maps provide average monthly and annual values of three evapotranspiration variables: point and areal evapotranspiration and areal actual evapotranspiration. The evapotranspiration estimates are based on the Morton relationship (Morton, 1983). However, these maps are not used day to day by the Bureau of Meteorology. Instead, a map of point values is provided showing 7-day ET0 sums, with monthly data also available, which is similar to the approach employed in Ireland.
3 Methodology

3.1 Study Area and Data

The study area was taken over the island of Ireland, using three downscaled NWP models, at three different spatial resolutions (1.5, 2 and 2.5 km). Two of the datasets were produced by researchers at the ICHEC, with nested domains, using the COSMO-CLM5 and WRF v3.7.1 models, and the third dataset, MÉRA, was produced by Met Éireann. MÉRA includes a data assimilation component, utilising time series of surface observations. An overview of the variables that are produced by each of these models is available in Appendix 1. Validation data for hydro-climate indices (ET\textsubscript{0}, ET\textsubscript{a}, SMD and SPI) were obtained from the Met Éireann network of synoptic stations (22 in total).

3.2 Methods and Bias Corrections

3.2.1 ET\textsubscript{0}

Reference evapotranspiration was calculated from the following RCM input variables: 2-m temperature, humidity/dew point temperature, 10-m wind speed, surface pressure and surface short-wave and long-wave radiation. As long-wave radiation was not available in the WRF model variables, it was calculated using the Julian day and solar declination methodology.

3.2.2 ET\textsubscript{0} bias correction

In their raw format, the variables produced from the NWP models have biases. Two approaches to correcting these biases were considered: bias correction of the constituent time series used in the estimation of ET\textsubscript{0} and an overall bias correction of the calculated ET\textsubscript{0} series.

A sensitivity analysis was undertaken to establish the sensitivity of the component variables of ET\textsubscript{0}. It was found that the most sensitive variables were humidity and radiation. Additionally, it was found that the errors in ET\textsubscript{0} using previously corrected input variables showed very little difference compared with raw input variables, with root mean square error (RMSE) differences of only ±0.01 mm. Therefore, ET\textsubscript{0} was calculated using raw model data and a correction factor was then applied to ET\textsubscript{0}.

Two correction methodologies were tested: bias correction and least squared estimator methods. The bias correction technique, developed by Hawkins et al. (2013), is given as:

\[
M_{bc} = O_{REF} + \left( \frac{\sigma_{O_{REF}}}{\sigma_{M_{REF}}} \right) (M_{REF}(t) - M_{REF})
\]  

where \(M_{bc}\) is the bias-corrected model, \(O_{REF}\) are the observations taken over a reference period and \(M_{REF}\) are the model data taken over the same reference period.

The advantages of this technique are its simplicity and the inclusion of standard deviations of both model and reference period. The second method, least squared estimator, is given as:

\[
\hat{a} = \frac{\sum_{n=1}^{N} x_n y_n - N \bar{x} \bar{y}}{\sum_{n=1}^{N} x_n^2 - N \bar{x}^2}
\]

\[
\hat{b} = \bar{y} - \hat{a} \bar{x}
\]

\[
\hat{y} = \hat{a} x + \hat{b}
\]

The variables \(x\) and \(y\) are the input model data and observational datasets, respectively, and \(\hat{y}\) is the corrected data or “line of best fit”. Of the two methods tested, it was determined that the least squared estimator method produced the lowest errors. As ET\textsubscript{0} varies considerably throughout the year, a best line fit for each month was derived. The regression analysis was carried out at all stations where ET\textsubscript{0} is calculated from meteorological observations (22 in total) and so a more complete countrywide profile was achieved. The locations of these stations are shown in Figure 3.1, with blue stations referring to those stations where data are available from 1981. The corrections were calculated for all stations for the period 2006 to present.

Once the regression coefficients \((a, b)\) were calculated at all stations, the values were interpolated onto the corresponding model grids. These gridded datasets were then used to correct the corresponding gridded ET\textsubscript{0} datasets. This method was repeated for each
month and applied to the full dataset (1981–2016). Figure 3.2, which presents yearly $ET_0$ sums for Dublin Airport and Valentia Observatory, shows the improvement of the corrected data compared with the raw output. For the raw WRF data, in particular, there was shown to be a consistent overestimation of $ET_0$ over the whole country, of between 50 and 100 mm depending on the station. Figure 3.3 shows the difference between the raw output and corrected $ET_0$ for Dublin Airport and Valentia.

### 3.2.3 $ET_a$ and SMDs

Time series of $ET_a$ and SMD were generated using the HSMD model. Inputs to the model were the bias-corrected $ET_0$ data and gridded observational precipitation datasets provided by Met Éireann. Observed rather than modelled precipitation data were used because of the uncertainties in precipitation in all three RCM models, and observed data were considered to provide a better representation of historical precipitation patterns. These data extended only to 2016 and so $ET_a$ and SMD series are limited to this date.

In order to start a HSMD model run, an initial value is required for SMD. Uncertainty in the initial model outputs can be reduced by initialising the model at a time when soils are at field capacity. In December 1980, there was a major rainfall event that caused all eight long-term synoptic stations in operation to be at field capacity. It was assumed that soils were at field capacity on this date across the country and so December 1980 was taken as the start time for the SMD model.

National datasets for $ET_a$ and SMD were derived for the five separate drainage classes described in the HSMD model. A single combined dataset was also produced, which used the Teagasc Indicative Soil Drainage Map for Ireland (Creamer et al., 2016) to assign a drainage type and corresponding $ET_a$ and SMD series to each grid square.
Figure 3.2. Raw output and corrected output for annual ET₀ sums at Dublin Airport and Valentia Observatory.

Figure 3.3. Difference in ET₀ yearly sums between corrected and original ET₀ values for Dublin Airport and Valentia Observatory.
4 Results and Validations

4.1 Reference Evapotranspiration

The primary variable analysed, ET$_0$, was calculated over multiple time periods. These include annual, seasonal, monthly and daily time periods, with both sums and averages calculated for the three models. The following sections will investigate the performance of all three models, which underwent correction using the methods described in Chapter 3. Following bias corrections, all models were found to perform with a high degree of accuracy and were in good agreement with observations. Prior to validation, it was expected that MÉRA would outperform both the WRF dataset and the COSMO-CLM dataset because of the advantage of data assimilation. The COSMO-CLM and WRF datasets were expected to add value because of the higher resolutions (1.5 km and 2 km, respectively) than in the MÉRA dataset (2.5 km).

4.1.1 Daily and annual analysis

The models were validated over a 37-year period (1981–2017) for COSMO-CLM and WRF and over a 36-year period for MÉRA (1981–2016) at 22 stations. As a result of the corrections, bias values were minimised. Table 4.1 shows the errors associated with daily ET$_0$ values for all three models. The MÉRA model outperformed both the WRF and the COSMO-CLM models for RMSE and correlation coefficients but was outperformed by the COSMO-CLM model for standard deviation. This is of less importance because of the variability of ET$_0$ throughout the course of the year. Analysis in the following sections investigates the variability in monthly values. Figure 4.1 shows scatter plots at Dublin Airport and Valentia Observatory.

As shown in Figure 4.1, the MÉRA data show the best fit, with the majority of values within 1 mm of the calculated values. The WRF and COSMO-CLM data are slightly more varied as shown in both Figure 4.1 and Table 4.1.

Among the more important tests is the performance of ET$_0$ on an annual basis and whether modelled values can pick up more abrupt changes. Figure 4.2 shows yearly sums of ET$_0$ at Dublin Airport and Valentia Observatory dating back to 1981. As mentioned previously, the corrections factors were generated using data from 2006 to 2017, with the resulting best line fits being applied back to 1981.

As shown in Figure 4.2, there is a good match between synoptic values and each of the models. For some stations, however, sudden drops or increases in ET$_0$ highlight an issue of the least squared

<table>
<thead>
<tr>
<th>Station</th>
<th>COSMO-CLM RMSE (mm)</th>
<th>WRF RMSE (mm)</th>
<th>MÉRA RMSE (mm)</th>
<th>COSMO-CLM Standard deviation (mm)</th>
<th>WRF Standard deviation (mm)</th>
<th>MÉRA Standard deviation (mm)</th>
<th>COSMO-CLM Correlation coefficient</th>
<th>WRF Correlation coefficient</th>
<th>MÉRA Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Belmullet</td>
<td>0.42</td>
<td>0.389</td>
<td>0.32</td>
<td>0.838</td>
<td>0.917</td>
<td>0.869</td>
<td>0.884</td>
<td>0.906</td>
<td>0.934</td>
</tr>
<tr>
<td>Casement</td>
<td>0.46</td>
<td>0.417</td>
<td>0.343</td>
<td>0.928</td>
<td>0.958</td>
<td>0.954</td>
<td>0.889</td>
<td>0.910</td>
<td>0.939</td>
</tr>
<tr>
<td>Cork Airport</td>
<td>0.495</td>
<td>0.432</td>
<td>0.395</td>
<td>0.934</td>
<td>0.964</td>
<td>0.98</td>
<td>0.884</td>
<td>0.913</td>
<td>0.928</td>
</tr>
<tr>
<td>Dublin Airport</td>
<td>0.451</td>
<td>0.418</td>
<td>0.343</td>
<td>0.912</td>
<td>0.927</td>
<td>0.949</td>
<td>0.893</td>
<td>0.909</td>
<td>0.939</td>
</tr>
<tr>
<td>Malin Head</td>
<td>0.422</td>
<td>0.398</td>
<td>0.321</td>
<td>0.719</td>
<td>0.826</td>
<td>0.775</td>
<td>0.861</td>
<td>0.884</td>
<td>0.922</td>
</tr>
<tr>
<td>Mullingar</td>
<td>0.426</td>
<td>0.390</td>
<td>0.330</td>
<td>0.941</td>
<td>0.959</td>
<td>0.967</td>
<td>0.911</td>
<td>0.926</td>
<td>0.948</td>
</tr>
<tr>
<td>Shannon Airport</td>
<td>0.455</td>
<td>0.430</td>
<td>0.362</td>
<td>0.959</td>
<td>1.057</td>
<td>0.989</td>
<td>0.904</td>
<td>0.918</td>
<td>0.941</td>
</tr>
<tr>
<td>Valentia</td>
<td>0.451</td>
<td>0.401</td>
<td>0.339</td>
<td>0.832</td>
<td>0.888</td>
<td>0.876</td>
<td>0.877</td>
<td>0.905</td>
<td>0.933</td>
</tr>
<tr>
<td>All</td>
<td>0.442</td>
<td>0.402</td>
<td>0.337</td>
<td>0.882</td>
<td>0.937</td>
<td>0.924</td>
<td>0.892</td>
<td>0.913</td>
<td>0.939</td>
</tr>
</tbody>
</table>

The best and worst performers are colour coded green and red, respectively.
estimator method being unable to correct distinct outliers. Nevertheless, all models are able to capture ET$_0$ to within 10% of values calculated from station measurements for all stations analysed. Table 4.2 shows associated errors in ET$_0$ for annual summed values for each station analysed above. The pattern is similar to the daily values presented in Table 4.1. However, the difference in ET$_0$ between the nested models (WRF, COSMO-CLM) and data-assimilated model (MÉRA) is small.

Figure 4.3 shows corrected maps of ET$_0$ for all three models and is one of the datasets provided for download. A breakdown of individual year sums for each model has also been produced. All three models show high values around coastlines, urban areas and the mouth of the Shannon River. The WRF model better resolves the urban centres because of the enhanced dynamics of its urban model. The MERA model shows a better fit to the calculated observations than the higher resolution models of COSMO-CLM and WRF.

### 4.1.2 Monthly and seasonal analysis

Analysis of monthly evapotranspiration values is of importance because of the variability of evapotranspiration throughout the year. Figures 4.4 and 4.5 show the average monthly sums of ET$_0$ at synoptic stations and countrywide, respectively.
Table 4.2. Errors in yearly summed values of ET₀ at selected stations from 1981 to 2017 using an overall weighted average across 22 stations

<table>
<thead>
<tr>
<th>Station</th>
<th>RMSE (mm)</th>
<th>Standard deviation (mm)</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>COSMO-CLM</td>
<td>WRF</td>
<td>MÉRA</td>
</tr>
<tr>
<td>Belmullet</td>
<td>23.646</td>
<td>23.565</td>
<td>20.479</td>
</tr>
<tr>
<td>Casement</td>
<td>20.844</td>
<td>17.937</td>
<td>15.279</td>
</tr>
<tr>
<td>Cork Airport</td>
<td>36.967</td>
<td>31.98</td>
<td>33.576</td>
</tr>
<tr>
<td>Dublin Airport</td>
<td>32.156</td>
<td>31.514</td>
<td>27.048</td>
</tr>
<tr>
<td>Malin Head</td>
<td>19.698</td>
<td>21.543</td>
<td>18.733</td>
</tr>
<tr>
<td>Mullingar</td>
<td>17.666</td>
<td>17.318</td>
<td>18.849</td>
</tr>
<tr>
<td>Shannon Airport</td>
<td>26.508</td>
<td>19.071</td>
<td>22.622</td>
</tr>
<tr>
<td>Valentia</td>
<td>26.868</td>
<td>24.485</td>
<td>19.757</td>
</tr>
<tr>
<td>All</td>
<td>24.164</td>
<td>21.293</td>
<td>20.402</td>
</tr>
</tbody>
</table>

The best and worst performers are colour coded green and red, respectively.

Figure 4.3. Average annual ET₀ maps for the COSMO-CLM and WRF (1981–2017) and MÉRA (1981–2016) models. The MÉRA model shows the best fit to observations and the WRF model performs the best of the higher resolution models.

Figure 4.4. Average monthly sums of ET₀ at selected stations for the WRF and COSMO-CLM (1981–2017) and MÉRA (1981–2016) models.
Figure 4.5. Average monthly sums of $\text{ET}_0$ for the WRF and COSMO-CLM (1981–2017) and MÉRA (1981–2016) models.
As shown in Figures 4.4 and 4.5, there is good agreement between models and calculated observations. The largest differences between models were noted around the Shannon region between April and July (see Figure 4.5). The WRF model produces the largest ET₀ value, with values approximately 10 mm greater than in the MÉRA model (see Figures 4.4 and 4.5). Averaging out the monthly sums and daily values for all stations gives the errors shown in Table 4.3. To quantify an overall view of the model performance, weighted averages are implemented, given by:

\[ x = \frac{\sum w_i x_i}{\sum w_i} \]

(4.1)

where \( x \) is the error at a station and \( w \) is the weight assigned to that station. Depending on the time period of the dataset at each station, a different weight is assigned. Those with data covering the full model time period (1981–2016) will have a higher weight and therefore exert more influence on the weighted average. With all stations considered, weighted averages show that MÉRA model outperforms the WRF model, which outperforms the COSMO-CLM model. For standard deviations, the COSMO-CLM model performs the best for 11 of the 12 months, and the MÉRA model is outperformed by both the WRF and the COSMO-CLM models for 10 months, reflecting the performance seen in the yearly sums of Table 4.2. For correlation coefficients, the MÉRA model performs best, followed by the WRF model.

### 4.2 Actual Evapotranspiration

Given the small error of the ET₀ series described in section 4.1, and the use of observational precipitation data, it follows that the corresponding ETₐ and SMD series would be a close match for observed records.

Actual evapotranspiration depends on the drainage of the soil, and at present there are five soil drainage types identified in Ireland, from excessively drained to poorly drained. A combined dataset for ETₐ was calculated using the Teagasc soil map to assign soil drainage classes to each grid square. However, the majority of datasets presented in the following sections show calculated soil moisture conditions using a single soil drainage type for each grid square.

The selection of synoptic stations used previously still applies for ETₐ; however, only well-drained, moderately drained and poorly drained soil drainage types are calculated from ET₀ and precipitation using the HSMD model at synoptic stations. Because of the nature of the model, ETₐ for moderately drained and well-drained soils was found to be nearly identical, so only well-drained and poorly drained soils are described in the following sections. Moderately drained soils are analysed in more detail in section 4.3 for SMDs.

#### 4.2.1 Well-drained soils

For well-drained soils, ETₐ is equal to ET₀ when the SMD at time \( t-1 \) is equal to 0. In the HSMD model, well-drained soils never saturate and remain at field

<table>
<thead>
<tr>
<th>Model</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COSMO-CLM</td>
<td>2.644</td>
<td>2.724</td>
<td>2.8</td>
<td>4.272</td>
<td>5.733</td>
<td>5.956</td>
<td>6.363</td>
<td>5.073</td>
<td>3.334</td>
<td>2.353</td>
<td>2.398</td>
<td>2.73</td>
</tr>
<tr>
<td>WRF</td>
<td>2.895</td>
<td>2.797</td>
<td>2.446</td>
<td>3.795</td>
<td>4.82</td>
<td>5.505</td>
<td>5.437</td>
<td>4.005</td>
<td>2.649</td>
<td>2.324</td>
<td>2.78</td>
<td>3.048</td>
</tr>
<tr>
<td>MÉRA</td>
<td>2.458</td>
<td>2.397</td>
<td>2.437</td>
<td>2.617</td>
<td>3.929</td>
<td>4.016</td>
<td>4.232</td>
<td>3.701</td>
<td>2.812</td>
<td>2.119</td>
<td>2.311</td>
<td>2.625</td>
</tr>
<tr>
<td>Daily</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COSMO-CLM</td>
<td>0.22</td>
<td>0.232</td>
<td>0.324</td>
<td>0.465</td>
<td>0.605</td>
<td>0.7</td>
<td>0.65</td>
<td>0.532</td>
<td>0.405</td>
<td>0.264</td>
<td>0.217</td>
<td>0.224</td>
</tr>
<tr>
<td>WRF</td>
<td>0.217</td>
<td>0.218</td>
<td>0.277</td>
<td>0.402</td>
<td>0.559</td>
<td>0.642</td>
<td>0.603</td>
<td>0.484</td>
<td>0.337</td>
<td>0.227</td>
<td>0.215</td>
<td>0.226</td>
</tr>
<tr>
<td>MÉRA</td>
<td>0.197</td>
<td>0.202</td>
<td>0.265</td>
<td>0.338</td>
<td>0.433</td>
<td>0.499</td>
<td>0.489</td>
<td>0.419</td>
<td>0.318</td>
<td>0.221</td>
<td>0.197</td>
<td>0.199</td>
</tr>
</tbody>
</table>

The best and worst performers are colour coded green and red, respectively.
capacity even on very wet days in winter. For all times when SMD>0 mm, ET_a is less than ET_o, and this has a large effect on the actual values. The difference in the well-drained soil ET_a value relative to the ET_o value varies substantially across the country, with the largest differences in the central and south-eastern regions. To the west and north, where it is generally wetter and more mountainous, the difference is smaller, as soil saturation is high enough to result in ET_a being equal to ET_o more often. Differences such as these have large effects on the outputs of models that require evapotranspiration as an input. This is reflected in Figure 4.6, which presents ET_o–ET_a at Dublin Airport. Encouragingly, most of the data points for all three models lie within 0.5 mm of a one-to-one relationship. The precipitation data used in the HSMD model (used in turn to produce ET_o values) extend to 2016 only. Figure 4.7 shows scatter plots of daily ET_a values at Dublin Airport.

Table 4.4 shows errors in the ET_a values for the eight long-term synoptic stations and overall weighted averages of all 22 stations. There is very little difference in the relative performance of the models, with the MÉRA model outperforming the WRF model, which in turn outperforms the COSMO-CLM model. As previously noted, the COSMO-CLM model performs best for standard deviations. Reflecting the decrease in ET_a values relative to ET_o, RMSE and standard deviation values have also decreased. Figure 4.8 shows yearly sums from 1981 to 2016 for Dublin Airport and Valentia Observatory.
High-resolution Gridded Datasets of Hydro-climate Indices for Ireland

Figure 4.8 shows a good match between all modelled \( \text{ET}_a \) and calculated \( \text{ET}_a \) values as derived through the HSMID model. Here, the errors are lower, with higher correlation coefficients also noted. Unlike for \( \text{ET}_0 \), where the models occasionally missed out on significant drops, for the most part modelled \( \text{ET}_a \) values are better represented. For the eight long-term synoptic stations, there is a consistent small increase in annual sums of 0.73–0.83 mm/year from 1981 to 2016. Table 4.5 shows an increase in these annual \( \text{ET}_a \) sums per year at each synoptic station, which estimated \( \text{ET}_0 \) back to 1981. This is particularly evident in stations such as Belmullet and Valentia in Figure 4.8.

As mentioned previously, there is an improvement in the performance of the models compared to the \( \text{ET}_0 \) equivalent, with a better fit and lower errors overall.

Table 4.4. Errors in yearly summed values of \( \text{ET}_a \) at selected stations and overall weighted averages for 22 stations from 1981 to 2016

<table>
<thead>
<tr>
<th>Station</th>
<th>RMSE (mm)</th>
<th>Standard deviation (mm)</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>COSMO-CLM</td>
<td>WRF</td>
<td>MÉRA</td>
</tr>
<tr>
<td>Belmullet</td>
<td>0.376</td>
<td>0.344</td>
<td>0.288</td>
</tr>
<tr>
<td>Casement</td>
<td>0.366</td>
<td>0.334</td>
<td>0.275</td>
</tr>
<tr>
<td>Cork Airport</td>
<td>0.418</td>
<td>0.38</td>
<td>0.334</td>
</tr>
<tr>
<td>Dublin Airport</td>
<td>0.363</td>
<td>0.341</td>
<td>0.279</td>
</tr>
<tr>
<td>Malin Head</td>
<td>0.376</td>
<td>0.356</td>
<td>0.291</td>
</tr>
<tr>
<td>Mullingar</td>
<td>0.357</td>
<td>0.33</td>
<td>0.276</td>
</tr>
<tr>
<td>Shannon Airport</td>
<td>0.375</td>
<td>0.358</td>
<td>0.298</td>
</tr>
<tr>
<td>Valentia</td>
<td>0.31</td>
<td>0.268</td>
<td>0.237</td>
</tr>
<tr>
<td>All</td>
<td>0.378</td>
<td>0.347</td>
<td>0.291</td>
</tr>
</tbody>
</table>

The best and worst performers are colour coded green and red, respectively.

Table 4.5. Increase in \( \text{ET}_a \) (mm/year) for each station for each model (1981–2016)

<table>
<thead>
<tr>
<th>Model</th>
<th>Belmullet</th>
<th>Casement</th>
<th>Cork Airport</th>
<th>Dublin Airport</th>
<th>Malin Head</th>
<th>Mullingar</th>
<th>Shannon Airport</th>
<th>Valentia</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>COSMO-CLM</td>
<td>0.532</td>
<td>0.753</td>
<td>0.626</td>
<td>0.586</td>
<td>0.732</td>
<td>0.785</td>
<td>1.115</td>
<td>0.710</td>
<td>0.730</td>
</tr>
<tr>
<td>WRF</td>
<td>0.512</td>
<td>0.836</td>
<td>0.494</td>
<td>0.562</td>
<td>0.843</td>
<td>0.807</td>
<td>1.082</td>
<td>0.769</td>
<td>0.738</td>
</tr>
<tr>
<td>MÉRA</td>
<td>0.588</td>
<td>0.735</td>
<td>0.810</td>
<td>0.581</td>
<td>0.640</td>
<td>0.973</td>
<td>1.223</td>
<td>1.134</td>
<td>0.836</td>
</tr>
</tbody>
</table>
as shown in Table 4.6. Regarding the overall average annual sums, there are large differences between ETa and ET0. This is further illustrated in Figure 4.9, with the highest values over to the west rather than the east as with ET0. However, it must be noted throughout that these datasets are not necessarily representative of the soil type at each location. The indicative ETa datasets, which use the Teagasc soil drainage datasets, are discussed in section 4.2.4. Annual sums for the eight long-term synoptic stations are shown in Figure 4.10 and average monthly sums across the country are shown in Figure 4.11.

Table 4.6. Errors in yearly summed values of ETa for well-drained soils at selected stations from 1981 to 2016 using an overall weighted average across 22 stations

<table>
<thead>
<tr>
<th>Station</th>
<th>RMSE (mm)</th>
<th>Standard deviation (mm)</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>COSMO-CLM</td>
<td>WRF</td>
<td>MÉRA</td>
</tr>
<tr>
<td>Belmullet</td>
<td>21.016</td>
<td>20.029</td>
<td>18.315</td>
</tr>
<tr>
<td>Casement</td>
<td>14.664</td>
<td>12.283</td>
<td>10.142</td>
</tr>
<tr>
<td>Cork Airport</td>
<td>25.403</td>
<td>24.385</td>
<td>25.59</td>
</tr>
<tr>
<td>Dublin Airport</td>
<td>20.423</td>
<td>20.496</td>
<td>18.182</td>
</tr>
<tr>
<td>Malin Head</td>
<td>18.137</td>
<td>17.918</td>
<td>17.225</td>
</tr>
<tr>
<td>Mullingar</td>
<td>10.429</td>
<td>10.018</td>
<td>10.856</td>
</tr>
<tr>
<td>Shannon Airport</td>
<td>17.514</td>
<td>15.667</td>
<td>14.781</td>
</tr>
<tr>
<td>Valentia</td>
<td>27.724</td>
<td>20.912</td>
<td>19.449</td>
</tr>
<tr>
<td>All</td>
<td>18.024</td>
<td>16.148</td>
<td>15.597</td>
</tr>
</tbody>
</table>

The best and worst performers are colour coded green and red, respectively.

Figure 4.9. Average annual ETa maps for well-drained soils for the COSMO-CLM, WRF and MÉRA models (1981–2016).

Figure 4.10. Average monthly sums of ETa for well-drained soils at Dublin Airport and Valentia Observatory for the COSMO-CLM, WRF and MÉRA models (1981–2016).
Figure 4.11. Average monthly sums of ET<sub>a</sub> for well-drained soils using the COSMO-CLM, WRF and MERA models (1981–2016).
As shown in Figures 4.10 and 4.11, there is a notable difference between ET_a and ET_0 across the country because of the lack of moisture in the soils during the summer months. During the winter months, as expected, there is very little difference noted between the models. During the summer months, particularly June and July, there is a notable difference between the WRF model and the other two models, which show higher values, particularly in the south and western regions. Table 4.7, which presents the errors on a monthly basis, shows that, once again, the MÉRA model is the best performer. Errors have also decreased for most months compared with the ET_0 equivalent of this table (see Table 4.3). Errors in monthly sums have decreased by over 1 mm during the summer months for all models and daily value errors have decreased by up to 0.15 mm during the summer months.

4.2.2 Poorly drained soils

The difference in evapotranspiration between well-drained and poorly drained soils varies across the country, from approximately 15 mm/year in mountainous regions in the north and west to 25 mm/year in the eastern and southern regions. As poorly drained soils hold more water than well-drained soils, yearly sums of ET_a are greater in poorly drained soils than in well-drained soils.

Tables 4.8 and 4.9 shows the errors for daily and yearly summed ET_a values for poorly drained soils, respectively. Validation results thus far have demonstrated that the MÉRA model consistently outperforms both the WRF model and the

Table 4.7. RMSEs of monthly summed ET_a and daily ET_a values for each month (1981–2016) using an overall weighted average across 22 stations for well-drained soils

<table>
<thead>
<tr>
<th>Station</th>
<th>Model</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MÉRA</td>
<td>2.453</td>
<td>2.281</td>
<td>2.291</td>
<td>2.145</td>
<td>2.788</td>
<td>3.094</td>
<td>2.950</td>
<td>2.854</td>
<td>2.251</td>
<td>1.914</td>
<td>2.263</td>
<td>2.579</td>
</tr>
<tr>
<td></td>
<td>Daily</td>
<td>0.217</td>
<td>0.227</td>
<td>0.306</td>
<td>0.426</td>
<td>0.514</td>
<td>0.567</td>
<td>0.510</td>
<td>0.446</td>
<td>0.353</td>
<td>0.249</td>
<td>0.212</td>
<td>0.224</td>
</tr>
<tr>
<td></td>
<td>COSMO-CLM</td>
<td>0.215</td>
<td>0.213</td>
<td>0.266</td>
<td>0.367</td>
<td>0.478</td>
<td>0.523</td>
<td>0.479</td>
<td>0.410</td>
<td>0.299</td>
<td>0.216</td>
<td>0.210</td>
<td>0.226</td>
</tr>
<tr>
<td></td>
<td>WRF</td>
<td>0.195</td>
<td>0.198</td>
<td>0.255</td>
<td>0.307</td>
<td>0.368</td>
<td>0.402</td>
<td>0.386</td>
<td>0.350</td>
<td>0.277</td>
<td>0.210</td>
<td>0.195</td>
<td>0.197</td>
</tr>
</tbody>
</table>

The best and worst performers are colour coded green and red, respectively.

Table 4.8. Errors in daily values of ET_a at selected stations and using overall weighted averages for 22 stations (1981–2016) for poorly drained soils

<table>
<thead>
<tr>
<th>Station</th>
<th>RMSE (mm)</th>
<th>Standard deviation (mm)</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>COSMO-CLM</td>
<td>WRF</td>
</tr>
<tr>
<td>Belmullet</td>
<td>0.396</td>
<td>0.377</td>
<td>0.329</td>
</tr>
<tr>
<td>Casement</td>
<td>0.386</td>
<td>0.352</td>
<td>0.297</td>
</tr>
<tr>
<td>Cork Airport</td>
<td>0.444</td>
<td>0.404</td>
<td>0.357</td>
</tr>
<tr>
<td>Dublin Airport</td>
<td>0.383</td>
<td>0.359</td>
<td>0.299</td>
</tr>
<tr>
<td>Malin Head</td>
<td>0.396</td>
<td>0.374</td>
<td>0.309</td>
</tr>
<tr>
<td>Mullingar</td>
<td>0.377</td>
<td>0.349</td>
<td>0.295</td>
</tr>
<tr>
<td>Shannon Airport</td>
<td>0.397</td>
<td>0.38</td>
<td>0.321</td>
</tr>
<tr>
<td>Valentia</td>
<td>0.431</td>
<td>0.384</td>
<td>0.329</td>
</tr>
<tr>
<td>All</td>
<td>0.399</td>
<td>0.368</td>
<td>0.313</td>
</tr>
</tbody>
</table>

The best and worst performers are colour coded green and red, respectively.
Table 4.9. Errors in yearly summed values of $\text{ET}_a$ at selected stations and using overall weighted averages for 22 stations (1981–2016) for poorly drained soils

<table>
<thead>
<tr>
<th>Station</th>
<th>RMSE (mm)</th>
<th>Standard deviation (mm)</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>COSMO-CLM</td>
<td>WRF</td>
<td>COSMO-CLM</td>
</tr>
<tr>
<td>Belmullet</td>
<td>35.263</td>
<td>31.564</td>
<td>34.649</td>
</tr>
<tr>
<td>Casement</td>
<td>14.107</td>
<td>11.866</td>
<td>12.732</td>
</tr>
<tr>
<td>Cork Airport</td>
<td>27.381</td>
<td>26.351</td>
<td>25.339</td>
</tr>
<tr>
<td>Dublin Airport</td>
<td>21.302</td>
<td>21.569</td>
<td>20.502</td>
</tr>
<tr>
<td>Malin Head</td>
<td>18.419</td>
<td>18.817</td>
<td>21.157</td>
</tr>
<tr>
<td>Mullingar</td>
<td>10.982</td>
<td>10.658</td>
<td>10.382</td>
</tr>
<tr>
<td>Shannon Airport</td>
<td>19.209</td>
<td>17.627</td>
<td>15.363</td>
</tr>
<tr>
<td>Valentia</td>
<td>28.444</td>
<td>22.061</td>
<td>23.781</td>
</tr>
<tr>
<td>All</td>
<td>20.034</td>
<td>18.111</td>
<td>19.229</td>
</tr>
</tbody>
</table>

The best and worst performers are colour coded green and red, respectively.

COSMO-CLM model. However, for yearly sums, the average RMSE best performer is the WRF model (a possible explanation is provided in section 4.3.3). As mentioned previously, $\text{ET}_a$ for poorly drained soils is expected to be greater than for well-drained soils and this is confirmed by Figure 4.12. The high evapotranspiration regions observed in the yearly well-drained soil maps of Figure 4.10 remain similar. The main difference is in the centre of the country, with values in the region of 30 mm/year greater than for well-drained soils. However, it must be stressed that these maps assume that all soils in the country are of the same drainage class and do not necessarily reflect the actual evapotranspiration at that location, so dataset end users must be aware of the regional drainage qualities of soil before utilising them at a specific location. Figure 4.13 shows the average monthly sums of $\text{ET}_a$ for poorly drained soils at Dublin

Figure 4.12. Average annual $\text{ET}_a$ maps for poorly drained soils for the COSMO-CLM, WRF and MÉRA models (1981–2016).

Figure 4.13. Average monthly sums of $\text{ET}_a$ for poorly drained soils at Dublin Airport and Valentia Observatory stations from 1981 to 2016.
Figure 4.14. Average monthly sums of ET_s for poorly drained soils using the COSMO-CLM, WRF and MERA models (1981–2016).
High-resolution Gridded Datasets of Hydro-climate Indices for Ireland

Airport and Valentia Observatory, Figure 4.14 shows the monthly sums countrywide for poorly drained soils and Table 4.10 shows RMSEs of monthly summed and daily ET\textsubscript{a} values for the same soil class for each month (1981–2016).

### 4.2.3 Excessively and imperfectly drained soils

Excessively and imperfectly drained soils are the newest additions to the Irish soil drainage classes, but SMDs for these drainage classes are not calculated from observed weather parameters at present. Figures 4.15 and 4.16 show the excessively and imperfectly

Table 4.10. RMSEs of monthly summed and daily ET\textsubscript{a} values for poorly drained soil for each month (1981–2016) using an overall weighted average across 22 stations

<table>
<thead>
<tr>
<th>Model</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COSMO-CLM</td>
<td>2.702</td>
<td>2.748</td>
<td>2.802</td>
<td>4.133</td>
<td>4.721</td>
<td>5.177</td>
<td>4.615</td>
<td>4.129</td>
<td>2.758</td>
<td>2.224</td>
<td>2.400</td>
<td>2.779</td>
</tr>
<tr>
<td>WRF</td>
<td>2.925</td>
<td>2.815</td>
<td>2.450</td>
<td>3.69</td>
<td>4.316</td>
<td>4.718</td>
<td>4.307</td>
<td>3.626</td>
<td>2.405</td>
<td>2.189</td>
<td>2.738</td>
<td>3.124</td>
</tr>
<tr>
<td>Daily</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COSMO-CLM</td>
<td>0.219</td>
<td>0.232</td>
<td>0.317</td>
<td>0.455</td>
<td>0.554</td>
<td>0.608</td>
<td>0.541</td>
<td>0.467</td>
<td>0.37</td>
<td>0.256</td>
<td>0.214</td>
<td>0.226</td>
</tr>
<tr>
<td>WRF</td>
<td>0.217</td>
<td>0.218</td>
<td>0.276</td>
<td>0.395</td>
<td>0.521</td>
<td>0.563</td>
<td>0.509</td>
<td>0.432</td>
<td>0.313</td>
<td>0.221</td>
<td>0.212</td>
<td>0.229</td>
</tr>
<tr>
<td>MÉRA</td>
<td>0.197</td>
<td>0.202</td>
<td>0.265</td>
<td>0.338</td>
<td>0.401</td>
<td>0.449</td>
<td>0.423</td>
<td>0.373</td>
<td>0.293</td>
<td>0.215</td>
<td>0.197</td>
<td>0.199</td>
</tr>
</tbody>
</table>

The best and worst performers are colour coded green and red, respectively.

Figure 4.15. Average annual ET\textsubscript{a} maps for excessively drained soils for the COSMO-CLM, WRF and MÉRA models (1981–2016).

Figure 4.16. Average annual ET\textsubscript{a} maps for imperfectly drained soils for the COSMO-CLM, WRF and MÉRA models (1981–2016).
drained average annual ET\textsubscript{a} sums, respectively. The imperfectly drained datasets shown in Figure 4.16 are very similar to the poorly drained datasets shown in Figure 4.12. This is because the only significant difference between the soils is the drainage term, which assumes maximum drainage for poorly and imperfectly drained soils of 0.5 and 3 mm, respectively. This equates to a difference of 5 mm/year on average.

4.2.4 Indicative ET\textsubscript{a} maps

Individual maps, prepared under the assumption that all areas are of the same drainage class, are useful if the user knows explicitly the type of soil at the specific location of interest. In a previous EPA project (Creamer et al., 2016), high-resolution soil property maps of Irish soils were prepared and sorted into their associated drainage classes. This dataset was acquired from Teagasc and scaled up to the resolution of the three models in the current study. The dataset contains all five soil drainage classes and also includes urban, bare rock and peat environments. These latter classes are not included in the current analysis as they are not classified under any drainage class. Figure 4.17 shows an indicative ET\textsubscript{a} map, which incorporates the spatially variable soil drainage classes. Although the enhanced spatial resolution of the WRF and COSMO-CLM models may have advantages for certain applications, based on the performance of the MÉRA model, we recommend that the ET\textsubscript{a} MÉRA dataset (as presented in Figure 4.17c) should be taken as an official national dataset for Ireland.

4.3 Soil Moisture Deficits

The following sections will investigate the performance of the HSMD model in the calculation of SMDs in well-drained, moderately drained and poorly drained soils. Because of the nature of the variable, summed values are not applicable, so monthly averages will be analysed. The number of field capacity days per year are also investigated and the results are presented in Appendix 2.

Figure 4.17. Average annual ET\textsubscript{a} maps incorporating the Teagasc National Soil Map of soil drainage classes for the COSMO-CLM, WRF and MÉRA models (1981–2016).
4.3.1 Well-drained SMD

For well-drained soils, the maximum SMD possible is 110 mm, although this is rarely observed in Ireland. Looking at overall daily values, as shown in Figure 4.18 and Table 4.11, the SMDs are in very good agreement with the synoptic values for all models, with all showing very high correlation coefficients.

The MÉRA model is marginally the better performer. A preliminary calculation of uncorrected SMDs, using modelled precipitation data as the input, resulted in poor correlations and skill scores. Therefore, it was decided to use Met Éireann observational precipitation gridded datasets, which results in a reliable and usable SMD dataset.

Figure 4.18. Scatter plots of daily SMD values for well-drained soils for Dublin Airport and Valentia Observatory for all models (1981–2016).

Table 4.11. Errors in daily values of SMDs (mm) (well drained) at selected stations from 1981 to 2016 using an overall weighted average across 22 stations

<table>
<thead>
<tr>
<th>Station</th>
<th>RMSE</th>
<th>Standard deviation</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>COSMO-CLM</td>
<td>WRF</td>
<td>MÉRA</td>
</tr>
<tr>
<td>Belmullet</td>
<td>2.256</td>
<td>2.335</td>
<td>2.066</td>
</tr>
<tr>
<td>Casement</td>
<td>2.686</td>
<td>2.696</td>
<td>2.609</td>
</tr>
<tr>
<td>Cork Airport</td>
<td>2.998</td>
<td>2.48</td>
<td>2.361</td>
</tr>
<tr>
<td>Dublin Airport</td>
<td>3.057</td>
<td>2.694</td>
<td>2.839</td>
</tr>
<tr>
<td>Malin Head</td>
<td>2.441</td>
<td>2.124</td>
<td>2.124</td>
</tr>
<tr>
<td>Mullingar</td>
<td>2.454</td>
<td>2.252</td>
<td>2.274</td>
</tr>
<tr>
<td>Shannon Airport</td>
<td>2.949</td>
<td>2.844</td>
<td>2.642</td>
</tr>
<tr>
<td>Valentia</td>
<td>2.48</td>
<td>2.158</td>
<td>2.152</td>
</tr>
<tr>
<td>All</td>
<td>2.615</td>
<td>2.375</td>
<td>2.299</td>
</tr>
</tbody>
</table>

The best and worst performers are colour coded green and red, respectively.
Figures 4.19–4.21 show yearly averages, monthly averages at synoptic stations and a comparison of monthly averages for all models for the whole country, respectively. Although monthly analysis is more relevant, yearly average datasets can help determine the drier regions. Figure 4.21 shows the similarity of SMD across the country using all three models for each month. As differences between models are so small, the higher resolution models, WRF and COSMO-CLM, can be used as a secondary option to

Figure 4.19. Average annual mean SMD maps for well-drained soils for the COSMO-CLM, WRF and MÉRA models (1981–2016).

Figure 4.20. SMD average monthly means for well-drained soils at Dublin Airport and Valentia Observatory (1981–2016).
Figure 4.21. Average monthly means of SMD for well-drained soils using the COSMO-CLM, WRF and MÉRA models (1981–2016).
the MÉRA model. This is further shown in Table 4.12, which shows weighted RMSE averages for monthly and daily values.

### 4.3.2 Moderately drained SMD

Moderately drained soils are most commonly found in the centre of the country and extend to the northern counties of Dublin and Louth. For moderately drained soils, the minimum SMD is −10 mm; soils may saturate on wet winter days but return to field capacity on the first dry day. RMSE errors are subsequently greater for moderately drained soils than for well-drained soils, as shown in Table 4.13.

For moderately drained soils, a small variability in errors is noted between models, with the WRF model outperforming the MÉRA model on occasion. The COSMO-CLM model is consistently outperformed by the other models for RMSE and correlation coefficients. Table 4.14 and Figure 4.22 demonstrate

<table>
<thead>
<tr>
<th>Model</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COSMO-CLM</td>
<td>0.374</td>
<td>0.754</td>
<td>0.893</td>
<td>1.434</td>
<td>2.219</td>
<td>2.998</td>
<td>2.912</td>
<td>2.875</td>
<td>2.457</td>
<td>1.166</td>
<td>0.389</td>
<td>0.377</td>
</tr>
<tr>
<td>WRF</td>
<td>0.411</td>
<td>0.81</td>
<td>0.877</td>
<td>1.3</td>
<td>1.918</td>
<td>2.554</td>
<td>2.452</td>
<td>2.301</td>
<td>1.966</td>
<td>1.069</td>
<td>0.512</td>
<td>0.454</td>
</tr>
<tr>
<td>MÉRA</td>
<td>0.339</td>
<td>0.668</td>
<td>0.796</td>
<td>1.274</td>
<td>1.84</td>
<td>2.354</td>
<td>2.24</td>
<td>2.301</td>
<td>2.077</td>
<td>1.027</td>
<td>0.407</td>
<td>0.407</td>
</tr>
<tr>
<td>Daily</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COSMO-CLM</td>
<td>0.642</td>
<td>1.132</td>
<td>1.628</td>
<td>2.333</td>
<td>3.07</td>
<td>3.995</td>
<td>3.77</td>
<td>3.842</td>
<td>3.338</td>
<td>1.892</td>
<td>0.765</td>
<td>0.677</td>
</tr>
<tr>
<td>WRF</td>
<td>0.675</td>
<td>1.145</td>
<td>1.542</td>
<td>2.155</td>
<td>2.801</td>
<td>3.556</td>
<td>3.427</td>
<td>3.35</td>
<td>2.909</td>
<td>1.782</td>
<td>0.863</td>
<td>0.767</td>
</tr>
<tr>
<td>MÉRA</td>
<td>0.591</td>
<td>1.014</td>
<td>1.489</td>
<td>2.127</td>
<td>2.705</td>
<td>3.353</td>
<td>3.246</td>
<td>3.329</td>
<td>3.015</td>
<td>1.758</td>
<td>0.758</td>
<td>0.701</td>
</tr>
</tbody>
</table>

The best and worst performers are colour coded green and red, respectively.

Table 4.13. Errors in daily values of SMD (mm) (moderately drained) at selected stations from 1981 to 2017 using an overall weighted average across 22 stations

<table>
<thead>
<tr>
<th>Station</th>
<th>RMSE</th>
<th>Standard deviation</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>COSMO-CLM</td>
<td>WRF</td>
<td>MÉRA</td>
</tr>
<tr>
<td>Belmullet</td>
<td>3.18</td>
<td>3.218</td>
<td>3.122</td>
</tr>
<tr>
<td>Casement</td>
<td>3.165</td>
<td>3.188</td>
<td>3.209</td>
</tr>
<tr>
<td>Cork Airport</td>
<td>3.822</td>
<td>3.404</td>
<td>3.373</td>
</tr>
<tr>
<td>Dublin Airport</td>
<td>3.457</td>
<td>3.311</td>
<td>3.180</td>
</tr>
<tr>
<td>Malin Head</td>
<td>3.21</td>
<td>2.996</td>
<td>3.033</td>
</tr>
<tr>
<td>Mullingar</td>
<td>3.115</td>
<td>2.904</td>
<td>2.943</td>
</tr>
<tr>
<td>Shannon Airport</td>
<td>3.545</td>
<td>3.459</td>
<td>3.467</td>
</tr>
<tr>
<td>Valentia</td>
<td>3.636</td>
<td>3.383</td>
<td>3.399</td>
</tr>
<tr>
<td>All</td>
<td>3.363</td>
<td>3.171</td>
<td>3.177</td>
</tr>
</tbody>
</table>

The best and worst performers are colour coded green and red, respectively.

Table 4.14. RMSEs of monthly average SMD (moderately drained) and daily values for each month (1981–2016) using an overall weighted average across 22 stations

<table>
<thead>
<tr>
<th>Model</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COSMO-CLM</td>
<td>0.492</td>
<td>0.84</td>
<td>0.908</td>
<td>1.463</td>
<td>2.224</td>
<td>3.097</td>
<td>2.922</td>
<td>2.812</td>
<td>2.398</td>
<td>1.172</td>
<td>0.491</td>
<td>0.525</td>
</tr>
<tr>
<td>WRF</td>
<td>0.558</td>
<td>0.912</td>
<td>0.916</td>
<td>1.375</td>
<td>1.896</td>
<td>2.54</td>
<td>2.427</td>
<td>2.299</td>
<td>1.921</td>
<td>1.113</td>
<td>0.634</td>
<td>0.63</td>
</tr>
<tr>
<td>MÉRA</td>
<td>0.485</td>
<td>0.77</td>
<td>0.909</td>
<td>1.322</td>
<td>1.974</td>
<td>2.374</td>
<td>2.604</td>
<td>2.279</td>
<td>2.021</td>
<td>1.081</td>
<td>0.513</td>
<td>0.562</td>
</tr>
<tr>
<td>Daily</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The best and worst performers are colour coded green and red, respectively.
Figure 4.22. Average monthly means of SMD for moderately drained soils using the COSMO-CLM, WRF and MERA models (1981–2016).
that all models have performed well and there is only a small difference in model errors. The monthly maps in Figure 4.22 show very little difference between models for all months.

### 4.3.3 Poorly drained SMD

For poorly drained soils, water surplus is drained at 0.5 mm/day, resulting in soils being at field capacity for larger portions of the year. Poorly drained soils are particularly common around Cavan, Leitrim, Limerick and Mayo. The change in water surplus and drainage rates results in a large difference between the model performance statistics. This is illustrated in the yearly averages shown in Figure 4.23, with the MÉRA model showing substantially lower SMDs than the WRF and COSMO-CLM models, particularly in the north and west. Table 4.15 shows that, in contrast to all previous analysis and tables, the MÉRA model is the worst performer because of having SMDs nearly consistently at field capacity during the winter months. To further emphasise the errors highlighted in Table 4.15, Figure 4.24 presents daily values of SMD for poorly drained soils at four locations. The scatter plots show large differences between the MÉRA model and the other two models, with the MÉRA model consistently underestimating the SMD. The poor performance of the MÉRA model for poorly drained soils may be attributed to the lower spatial resolution of the MÉRA data or the transformation of 1-km gridded precipitation to a 2.5-km grid.

![Figure 4.23. Average annual mean SMD maps for poorly drained soils for the COSMO-CLM, WRF and MÉRA models (1981–2016).](image)

![Table 4.15. Errors in daily values of SMD (poorly drained) at selected stations from 1981 to 2016 using an overall weighted average across 22 stations](table)

<table>
<thead>
<tr>
<th>Station</th>
<th>RMSE COSMO-CLM</th>
<th>RMSE WRF</th>
<th>RMSE MÉRA</th>
<th>Standard deviation COSMO-CLM</th>
<th>Standard deviation WRF</th>
<th>Standard deviation MÉRA</th>
<th>Correlation coefficient COSMO-CLM</th>
<th>Correlation coefficient WRF</th>
<th>Correlation coefficient MÉRA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Belmullet</td>
<td>2.752</td>
<td>2.93</td>
<td>3.945</td>
<td>14.774</td>
<td>16.038</td>
<td>14.69</td>
<td>0.983</td>
<td>0.991</td>
<td>0.974</td>
</tr>
<tr>
<td>Casement</td>
<td>3.111</td>
<td>3.115</td>
<td>5.205</td>
<td>23.031</td>
<td>23.353</td>
<td>23.263</td>
<td>0.991</td>
<td>0.991</td>
<td>0.983</td>
</tr>
<tr>
<td>Cork Airport</td>
<td>3.423</td>
<td>2.858</td>
<td>4.617</td>
<td>17.843</td>
<td>18.705</td>
<td>18.649</td>
<td>0.988</td>
<td>0.989</td>
<td>0.981</td>
</tr>
<tr>
<td>Dublin Airport</td>
<td>3.317</td>
<td>2.944</td>
<td>4.868</td>
<td>20.245</td>
<td>20.582</td>
<td>21.309</td>
<td>0.990</td>
<td>0.992</td>
<td>0.985</td>
</tr>
<tr>
<td>Malin Head</td>
<td>2.776</td>
<td>2.542</td>
<td>4.341</td>
<td>14.558</td>
<td>15.694</td>
<td>14.878</td>
<td>0.986</td>
<td>0.987</td>
<td>0.976</td>
</tr>
<tr>
<td>Mullingar</td>
<td>2.853</td>
<td>2.664</td>
<td>4.272</td>
<td>17.956</td>
<td>18.176</td>
<td>18.155</td>
<td>0.990</td>
<td>0.991</td>
<td>0.985</td>
</tr>
<tr>
<td>Shannon Airport</td>
<td>3.569</td>
<td>3.528</td>
<td>4.905</td>
<td>20.692</td>
<td>21.767</td>
<td>21.192</td>
<td>0.987</td>
<td>0.987</td>
<td>0.981</td>
</tr>
<tr>
<td>Valentia</td>
<td>2.896</td>
<td>2.493</td>
<td>3.754</td>
<td>13.121</td>
<td>14.209</td>
<td>13.426</td>
<td>0.981</td>
<td>0.985</td>
<td>0.976</td>
</tr>
<tr>
<td>All</td>
<td>3.149</td>
<td>2.886</td>
<td>4.470</td>
<td>16.864</td>
<td>17.671</td>
<td>17.297</td>
<td>0.985</td>
<td>0.987</td>
<td>0.977</td>
</tr>
</tbody>
</table>

The best and worst performers are colour coded green and red, respectively.
Figure 4.24. Scatter plots of daily SMD values for poorly drained soils at Dublin Airport and Valentia Observatory for all models (1981–2016).

Figure 4.25 highlights the negative bias of monthly MÉRA SMD values, with the largest underestimations noted for the winter months. Countrywide weighted averages for monthly and daily values are shown in Table 4.16, with errors in the MÉRA model consistently higher than those in the WRF and COSMO-CLM models. Despite this, as the MÉRA model is the best performer across all other drainage classes and

Table 4.25. Average monthly SMD means for poorly drained soils at Dublin Airport and Valentia Observatory (1981–2016).

Table 4.16 RMSEs of monthly average SMD (poorly drained) and daily values for each month (1981–2016) using an overall weighted average across 22 stations

<table>
<thead>
<tr>
<th>Model</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COSMO-CLM</td>
<td>0.577</td>
<td>0.713</td>
<td>1.001</td>
<td>1.731</td>
<td>2.599</td>
<td>3.561</td>
<td>3.468</td>
<td>3.574</td>
<td>3.159</td>
<td>1.529</td>
<td>0.454</td>
<td>0.383</td>
</tr>
<tr>
<td>WRF</td>
<td>0.635</td>
<td>0.765</td>
<td>0.957</td>
<td>1.616</td>
<td>2.343</td>
<td>3.15</td>
<td>2.995</td>
<td>2.91</td>
<td>2.586</td>
<td>1.381</td>
<td>0.558</td>
<td>0.486</td>
</tr>
<tr>
<td>MÉRA</td>
<td>2.017</td>
<td>3.318</td>
<td>4.28</td>
<td>4.557</td>
<td>4.204</td>
<td>3.92</td>
<td>3.902</td>
<td>3.904</td>
<td>3.865</td>
<td>3.54</td>
<td>2.083</td>
<td>2.012</td>
</tr>
<tr>
<td>Daily</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COSMO-CLM</td>
<td>0.965</td>
<td>1.262</td>
<td>1.857</td>
<td>2.683</td>
<td>3.552</td>
<td>4.661</td>
<td>4.498</td>
<td>4.674</td>
<td>4.174</td>
<td>2.522</td>
<td>1.054</td>
<td>0.937</td>
</tr>
<tr>
<td>MÉRA</td>
<td>2.601</td>
<td>4.211</td>
<td>5.256</td>
<td>5.18</td>
<td>4.901</td>
<td>4.803</td>
<td>4.941</td>
<td>4.861</td>
<td>4.795</td>
<td>4.554</td>
<td>2.816</td>
<td>2.88</td>
</tr>
</tbody>
</table>

The best and worst performers are colour coded green and red, respectively.
Figure 4.26. Average monthly means of SMD for poorly drained soils using the COSMO-CLM, WRF and MÉRA models (1981–2016).
demonstrates the highest skill in the representation of ET₀ and ETₐ, the MÉRA dataset should still be considered as the definitive SMD dataset for Ireland. Figure 4.26 shows comparisons of monthly means of poorly drained SMDs across the whole country.

As discussed throughout this section, in contrast to well-drained and moderately drained soils, the MÉRA model has not performed as well for poorly drained soils. This is highlighted further in Figure 4.27, which shows daily SMDs for the three drainage classes analysed at Dublin Airport. The bottom right window of Figure 4.27 shows a greater proportion of underestimated values for the MÉRA model compared with the COSMO-CLM and WRF models. These errors should be taken into account when utilising the MÉRA poorly drained soils dataset, and in particular the indicative SMD dataset.

4.3.4 Excessively and imperfectly drained SMD

Similarly to ET₀, excessively and imperfectly drained SMDs calculated from observed meteorological values are not currently available and it is therefore not possible to validate the models. Excessively drained soils have a SMD limit of 50 mm and are confined to a small area around Wexford. Imperfectly drained soils have a maximum drainage of 3 mm and are confined to areas in Wicklow, Laois and Westmeath. Figures 4.28 and 4.29 show annual average SMD maps for excessively and imperfectly drained soils, respectively.

![Figure 4.27. Comparison of daily SMDs for (A) well-drained, (B) moderately drained and (C) poorly drained soils for Dublin Airport (1981–2016).](image)
Figure 4.28. Average annual mean SMD maps for excessively drained soils for the COSMO-CLM, WRF and MÉRA models (1981–2016).

Figure 4.29. Average annual mean SMD maps for imperfectly drained soils for the COSMO-CLM, WRF and MÉRA models (1981–2016).

4.3.5. **Indicative SMD maps**

As with ET<sub>a</sub> SMD datasets were derived using the Teagasc Indicative Soil Drainage Maps. Knowledge of the soil drainage class at the location of interest is required by the end user prior to utilising these datasets. Figure 4.30 shows indicative SMD maps for all drainage classes for each month.
Figure 4.30. Mean monthly SMD incorporating the Teagasc National Soil Map of soil drainage classes using the WRF, COSMO-CLM and MERA models (1981–2016).
4.4 Standardised Precipitation Index

The SPI has been derived for Ireland using gridded observational datasets of precipitation.

Grided datasets have been produced for the period 1981–2016 (an example of which is shown in Figure 4.31 for December 2016) at 1-, 2-, 3-, 6-, 12- and 24-month timescales.

Additionally, a script has been written allowing the end user to enter a latitude and longitude of interest and return the SPI values at that location for 1981–2016. An example of the output is provided in Figure 4.32. Additional station plots are presented in Appendix 2. The SPI script is shown in Appendix 3.

![Gridded SPI sample for December 2016 for six different timescales.](image)

**Figure 4.31.** Gridded SPI sample for December 2016 for six different timescales.

![SPI sample focused on Valentia Observatory for 1 month and 24 months.](image)

**Figure 4.32.** SPI sample focused on Valentia Observatory for 1 month and 24 months.
4.5 Agroclimatic Atlas of Ireland

In 1996, Collins and Cummins produced the Agroclimatic Atlas of Ireland, which included maps of Irish agricultural climatology and geomorphology. One of the project aims was to facilitate an update to these maps.

Met Éireann provided historical gridded datasets of precipitation and temperature at 1-km resolution from 1981 to 2016. For all agro-climatic variables, the 30-year period 1981–2010 is considered, corresponding to the current climate normals. The large network of temperature and precipitation observations allowed for the development of such high-resolution datasets. The agro-climatic variables that have been derived to facilitate an update of the Agroclimatic Atlas of Ireland are as follows:

1. mean annual precipitation;
2. mean monthly precipitation;
3. number of wet days per year (varying thresholds);
4. mean daily temperatures;
5. mean monthly temperatures;
6. maximum/minimum temperatures for specific months;
7. number of frost days;
8. $\text{ET}_0$;
9. $\text{ET}_a$;
10. SMDs;
11. number of field capacity days (derived from the MÉRA dataset);
12. growing season length and start and end dates;
13. SPI (varying thresholds).

Unless stated otherwise, all datasets were derived using the Met Éireann observed gridded rainfall and temperature datasets with 1-km grid spacings. For more detail and maps of the gridded datasets above, see Appendix 2.
5 Conclusions and Recommendations

High-resolution gridded datasets of \( \text{ET}_0 \), \( \text{ET}_a \) and SMDs have been produced using inputs from three RCMs. \( \text{ET}_0 \) was calculated using RCM data as input to the FAO Penman–Monteith equation, in line with international best practice and the current \( \text{ET}_0 \) calculation method used by Met Éireann. The datasets were validated against Met Éireann synoptic station measurements and outputs of a SMD model at 22 locations across the country. Of the three RCM datasets analysed, COSMO-CLM5, WRF v3.7.1 and MÉRA, the MÉRA model has been shown to be the best performer across most categories. The advantage of the MÉRA model can largely be attributed to the inclusion of data assimilation during model simulation. It is recommended that the reference gridded national datasets for \( \text{ET}_0 \), \( \text{ET}_a \) and SMD are those derived from the MÉRA dataset.

However, despite the WRF and COSMO-CLM models not performing as well as the MÉRA model, both datasets complement the MÉRA model well in estimating the hydro-climate variables and have the advantage of higher resolution (2 km and 1.5 km, respectively) than the MÉRA model (2.5 km). This advantage was highlighted when validating SMDs for poorly drained soils, with the MÉRA model underestimating SMDs for the winter months, resulting in higher errors. For climate studies and academic purposes, the WRF dataset is recommended as the next best option, having the next lowest errors and correlation coefficients. However, for a definitive dataset for each variable and to avoid internal inconsistencies, particularly with the combined maps and datasets, it is recommended that the MÉRA dataset should be used.

The research also facilitated an update of the Agroclimatic Atlas of Ireland, by preparing a number of additional datasets using Met Éireann gridded observational datasets of temperature and precipitation. The derived agro-climate datasets include the number of wet days at different thresholds (1, 5, 10, 15, 20, 30 mm), the number of frost days, growing season lengths and the SPI at varying time intervals.

The research described in this report is based solely on calculated values for evapotranspiration and does not include validation against direct observations. The lack of adequate observational infrastructure for evapotranspiration and soil moisture conditions has been recognised as a significant limitation and source of uncertainty in hydro-meteorological studies in Ireland. Developing such infrastructure would be of great benefit to future hydro-climate research in Ireland, as well as providing baseline data for the future assessment and development of the methodologies and datasets described in this report.
References


### Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CHESS</td>
<td>Climate, Hydrological and Ecological research Support System</td>
</tr>
<tr>
<td>ET&lt;sub&gt;0&lt;/sub&gt;</td>
<td>Reference evapotranspiration</td>
</tr>
<tr>
<td>ET&lt;sub&gt;a&lt;/sub&gt;</td>
<td>Actual evapotranspiration</td>
</tr>
<tr>
<td>FAO</td>
<td>Food and Agriculture Organization of the United Nations</td>
</tr>
<tr>
<td>HSMD</td>
<td>Hybrid soil moisture deficit</td>
</tr>
<tr>
<td>ICHEC</td>
<td>Irish Centre for High-End Computing</td>
</tr>
<tr>
<td>JULES</td>
<td>Joint UK Land Environment Simulator</td>
</tr>
<tr>
<td>MÉRA</td>
<td>Met Éireann Re-Analysis</td>
</tr>
<tr>
<td>MORECS</td>
<td>Meteorological Office Rainfall and Evaporation Calculation System</td>
</tr>
<tr>
<td>NWP</td>
<td>Numerical weather prediction</td>
</tr>
<tr>
<td>PFRA</td>
<td>Preliminary Flood Risk Assessment</td>
</tr>
<tr>
<td>RCM</td>
<td>Regional climate NWP model</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root mean square error</td>
</tr>
<tr>
<td>RS</td>
<td>Remote sensing</td>
</tr>
<tr>
<td>SMD</td>
<td>Soil moisture deficit</td>
</tr>
<tr>
<td>SPEI</td>
<td>Standardised Precipitation Evapotranspiration Index</td>
</tr>
<tr>
<td>SPI</td>
<td>Standardised Precipitation Index</td>
</tr>
<tr>
<td>USGS</td>
<td>US Geological Survey</td>
</tr>
<tr>
<td>WRF</td>
<td>Weather Research and Forecasting</td>
</tr>
</tbody>
</table>
## Appendix 1  List of Archived Variables from Each Model

### Table A1.1. List of variables from the COSMO-CLM5 dataset produced by ICHEC researchers

<table>
<thead>
<tr>
<th>Variable</th>
<th>Units</th>
<th>Variable</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surface pressure</td>
<td>Pa</td>
<td>Surface lifted index</td>
<td>K</td>
</tr>
<tr>
<td>Mean sea level pressure</td>
<td>Pa</td>
<td>Showalter Index</td>
<td>K</td>
</tr>
<tr>
<td>Surface temperature</td>
<td>K</td>
<td>Surface net downward SW radiation</td>
<td>W/m²</td>
</tr>
<tr>
<td>2-m temperature</td>
<td>K</td>
<td>Averaged surface net downward SW radiation</td>
<td>W/m²</td>
</tr>
<tr>
<td>2-m dew point temperature</td>
<td>K</td>
<td>Direct surface downward SW radiation</td>
<td>W/m²</td>
</tr>
<tr>
<td>U-component of 10-m wind</td>
<td>m/s</td>
<td>Averaged direct surface downward SW radiation</td>
<td>W/m²</td>
</tr>
<tr>
<td>V-component of 10-m wind</td>
<td>m/s</td>
<td>Averaged surface diffuse downward SW radiation</td>
<td>W/m²</td>
</tr>
<tr>
<td>Surface roughness length</td>
<td>m</td>
<td>Averaged surface diffuse upward SW radiation</td>
<td>W/m²</td>
</tr>
<tr>
<td>Maximum 10-m wind speed</td>
<td>m/s</td>
<td>Averaged downward LW radiation at the surface</td>
<td>W/m²</td>
</tr>
<tr>
<td>Surface specific humidity</td>
<td>kg/kg</td>
<td>Averaged upward LW radiation at the surface</td>
<td>W/m²</td>
</tr>
<tr>
<td>2-m specific humidity</td>
<td>kg/kg</td>
<td>Averaged surface net downward LW radiation</td>
<td>W/m²</td>
</tr>
<tr>
<td>2-m relative humidity</td>
<td>%</td>
<td>Averaged surface photosynthetic active radiation</td>
<td>W/m²</td>
</tr>
<tr>
<td>Snow surface temperature</td>
<td>K</td>
<td>Surface albedo</td>
<td>0–1</td>
</tr>
<tr>
<td>Thickness of snow</td>
<td>m</td>
<td>Surface latent heat flux</td>
<td>W/m²</td>
</tr>
<tr>
<td>Height of freezing level</td>
<td>m</td>
<td>Surface sensible heat flux</td>
<td>W/m²</td>
</tr>
<tr>
<td>Precipitation rate</td>
<td>kg/m²/s</td>
<td>Surface evaporation</td>
<td>kg/m²</td>
</tr>
<tr>
<td>Large-scale rainfall</td>
<td>kg/m²</td>
<td>Total precipitation amount</td>
<td>kg/m²</td>
</tr>
<tr>
<td>Convective rainfall</td>
<td>kg/m²</td>
<td>Soil temperature (eight levels)</td>
<td>K</td>
</tr>
<tr>
<td>Large-scale snowfall</td>
<td>kg/m²</td>
<td>Soil water content (eight levels)</td>
<td>m</td>
</tr>
<tr>
<td>Convective snowfall</td>
<td>kg/m²</td>
<td>Daily average 2-m temperature</td>
<td>K</td>
</tr>
<tr>
<td>Large-scale graupel</td>
<td>kg/m²</td>
<td>Daily maximum 2-m temperature</td>
<td>K</td>
</tr>
<tr>
<td>Surface run-off</td>
<td>kg/m²</td>
<td>Daily minimum 2-m temperature</td>
<td>K</td>
</tr>
<tr>
<td>Subsurface run-off</td>
<td>kg/m²</td>
<td>Daily duration of sunshine</td>
<td>s</td>
</tr>
<tr>
<td>Vertical integrated water vapour</td>
<td>kg/m²</td>
<td>Daily relative duration of sunshine</td>
<td>s</td>
</tr>
<tr>
<td>Vertical integrated cloud ice</td>
<td>kg/m²</td>
<td>Below variables archived at 20, 40, … 200 m:</td>
<td></td>
</tr>
<tr>
<td>Vertical integrated cloud water</td>
<td>kg/m²</td>
<td>U-component of wind</td>
<td>m/s</td>
</tr>
<tr>
<td>Total cloud cover</td>
<td>0–1</td>
<td>V-component of wind</td>
<td>m/s</td>
</tr>
<tr>
<td>Low cloud cover</td>
<td>0–1</td>
<td>Air density</td>
<td>kg/m³</td>
</tr>
<tr>
<td>Medium cloud cover</td>
<td>0–1</td>
<td>Wind speed</td>
<td>m/s</td>
</tr>
<tr>
<td>High cloud cover</td>
<td>0–1</td>
<td>Cube wind speed</td>
<td>m³/s³</td>
</tr>
<tr>
<td>CAPE 3 km</td>
<td>J/kg</td>
<td>Wind direction</td>
<td>Degrees</td>
</tr>
</tbody>
</table>

CAPE, convective available potential energy; LW, long wave; SW, short wave.
Table A1.2. List of variables from the WRF dataset (v 3.7.1) produced by ICHEC researchers

<table>
<thead>
<tr>
<th>Variable</th>
<th>Units</th>
<th>Variable</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surface temperature</td>
<td>K</td>
<td>Air density at lowest model level</td>
<td>kg/m$^3$</td>
</tr>
<tr>
<td>Surface pressure</td>
<td>Pa</td>
<td>U-component of wind (Earth) at 40, 60, 80, 100, 120 m</td>
<td>m/s</td>
</tr>
<tr>
<td>Sea level pressure</td>
<td>Pa</td>
<td>V-component of wind (Earth) at 40, 60, 80, 100, 120 m</td>
<td>m/s</td>
</tr>
<tr>
<td>Sea level pressure</td>
<td>Pa</td>
<td>SW flux downward at surface instant</td>
<td>W/m$^2$</td>
</tr>
<tr>
<td>2-m temperature</td>
<td>°C</td>
<td>SW flux downward at surface accumulated</td>
<td>W/m$^2$</td>
</tr>
<tr>
<td>Total cloud fraction</td>
<td>0–1</td>
<td>Bucket SW flux downward at surface accumulated</td>
<td>W/m$^2$</td>
</tr>
<tr>
<td>Time varying roughness height</td>
<td>m</td>
<td>Friction velocity</td>
<td>m/s</td>
</tr>
<tr>
<td>Water vapour mixing ratio at 2 m</td>
<td>kg/kg</td>
<td>Liquid path water</td>
<td>kg/m$^2$</td>
</tr>
<tr>
<td>Relative humidity at 2 m</td>
<td>%</td>
<td>Ice path water</td>
<td>kg/m$^2$</td>
</tr>
<tr>
<td>U-component of wind at 10 m</td>
<td>m/s</td>
<td>Ground heat flux</td>
<td>W/m$^2$</td>
</tr>
<tr>
<td>V-component of wind at 10 m</td>
<td>m/s</td>
<td>Physical snow depth</td>
<td>m</td>
</tr>
<tr>
<td>Maximum 10-m wind speed previous output time</td>
<td>m/s</td>
<td>Water evaporation flux at surface</td>
<td>kg/m$^2$</td>
</tr>
<tr>
<td>Total precipitation</td>
<td>mm</td>
<td>Soil temperature, at four levels</td>
<td>K</td>
</tr>
<tr>
<td>Accumulated snowfall</td>
<td>mm</td>
<td>Soil moisture, at four levels</td>
<td>m$^3$/m$^3$</td>
</tr>
</tbody>
</table>

SW, short wave.

Table A1.3. List of variables from the MÉRA dataset produced by Met Éireann

<table>
<thead>
<tr>
<th>Variable</th>
<th>Units</th>
<th>Variable</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surface pressure</td>
<td>Pa</td>
<td>Cloud base</td>
<td>m</td>
</tr>
<tr>
<td>Mean sea level pressure</td>
<td>Pa</td>
<td>Cloud top</td>
<td>m</td>
</tr>
<tr>
<td>Surface temperature</td>
<td>K</td>
<td>Momentum flux, v-component</td>
<td>N/m$^2$</td>
</tr>
<tr>
<td>2-m temperature</td>
<td>K</td>
<td>Momentum flux, u-component</td>
<td>N/m$^2$</td>
</tr>
<tr>
<td>2-m relative humidity</td>
<td>%</td>
<td>Height of $T_{w} = 0$ isotherm</td>
<td>m</td>
</tr>
<tr>
<td>U-component of 10-m wind</td>
<td>m/s</td>
<td>Height of 0° isotherm</td>
<td>m</td>
</tr>
<tr>
<td>V-component of 10-m wind</td>
<td>m/s</td>
<td>Total precipitation</td>
<td>kg/m$^2$</td>
</tr>
<tr>
<td>Total cloud cover</td>
<td>0–1</td>
<td>Rain</td>
<td>kg/m$^2$</td>
</tr>
<tr>
<td>High cloud cover</td>
<td>0–1</td>
<td>Graupel</td>
<td>kg/m$^2$</td>
</tr>
<tr>
<td>Medium cloud cover</td>
<td>0–1</td>
<td>Snow</td>
<td>kg/m$^2$</td>
</tr>
<tr>
<td>Low cloud cover</td>
<td>0–1</td>
<td>Sensible heat flux</td>
<td>J/m$^2$</td>
</tr>
<tr>
<td>Mixed layer depth</td>
<td>m</td>
<td>Latent heat flux of evaporation</td>
<td>J/m$^2$</td>
</tr>
<tr>
<td>Direct SW irradiance</td>
<td>W/m$^2$</td>
<td>Latent heat flux of sublimation</td>
<td>J/kg</td>
</tr>
<tr>
<td>LW irradiance</td>
<td>W/m$^2$</td>
<td>Water evaporation</td>
<td>kg/m$^2$</td>
</tr>
<tr>
<td>Snow depth</td>
<td>kg/m$^2$</td>
<td>Snow sublimation</td>
<td>kg/m$^2$</td>
</tr>
<tr>
<td>Total cloud cover (fog)</td>
<td>0–1</td>
<td>Net SW irradiance</td>
<td>J/m$^2$</td>
</tr>
<tr>
<td>Visibility</td>
<td>m</td>
<td>Net LW irradiance</td>
<td>J/m$^2$</td>
</tr>
<tr>
<td>Icing index</td>
<td>–</td>
<td>Direct SW irradiance</td>
<td>J/m$^2$</td>
</tr>
<tr>
<td>Precipitation type</td>
<td>–</td>
<td>LW irradiance</td>
<td>J/m$^2$</td>
</tr>
<tr>
<td>Global irradiance</td>
<td>J/m$^2$</td>
<td>U-component of wind</td>
<td>m/s</td>
</tr>
<tr>
<td>Direct normal irradiance</td>
<td>J/m$^2$</td>
<td>V-component of wind</td>
<td>m/s</td>
</tr>
<tr>
<td>Lightning</td>
<td>m$^3$</td>
<td>Vertical velocity</td>
<td>m/s</td>
</tr>
</tbody>
</table>
Table A1.3. Continued

<table>
<thead>
<tr>
<th>Variable</th>
<th>Units</th>
<th>Variable</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hail diagnostic</td>
<td>kg/m²</td>
<td>Relative humidity</td>
<td>%</td>
</tr>
<tr>
<td>Maximum temperature</td>
<td>K</td>
<td>Cloud ice</td>
<td>kg/m²</td>
</tr>
<tr>
<td>Minimum temperature</td>
<td>K</td>
<td>Cloud water</td>
<td>kg/m²</td>
</tr>
<tr>
<td>Gust, u-component</td>
<td>m/s</td>
<td>Cloud top temperature (infrared)</td>
<td>K</td>
</tr>
<tr>
<td>Gust, v-component</td>
<td>m/s</td>
<td>Tₚ (water vapour)</td>
<td>K</td>
</tr>
<tr>
<td>Direct SW irradiance</td>
<td>J/m²</td>
<td>Tₚ (water vapour)+ cloud correction</td>
<td>K</td>
</tr>
<tr>
<td>Net SW irradiance</td>
<td>J/m²</td>
<td>Cloud water reflectivity (visible)</td>
<td>–</td>
</tr>
<tr>
<td>Net SW irradiance (accumulated)</td>
<td>J/m²</td>
<td>Precipitable water</td>
<td>kg/m²</td>
</tr>
<tr>
<td>Net LW irradiance</td>
<td>J/m²</td>
<td>Rain</td>
<td>kg/m²</td>
</tr>
<tr>
<td>Net LW irradiance (accumulated)</td>
<td>J/m²</td>
<td>Snow</td>
<td>kg/m²</td>
</tr>
<tr>
<td>Temperature</td>
<td>K</td>
<td>Graupel</td>
<td>kg/m²</td>
</tr>
<tr>
<td>U-component of wind</td>
<td>m/s</td>
<td>Cloud ice</td>
<td>kg/m²</td>
</tr>
<tr>
<td>V-component of wind</td>
<td>m/s</td>
<td>Cloud water</td>
<td>kg/m²</td>
</tr>
<tr>
<td>Relative humidity</td>
<td>%</td>
<td>Soil temperature (two levels)</td>
<td>J/m²</td>
</tr>
<tr>
<td>Geopotential</td>
<td>m²/s²</td>
<td>Soil moisture content (three levels)</td>
<td>J/m²</td>
</tr>
<tr>
<td>Precipitation type</td>
<td>K</td>
<td>Surface soil ice (three levels)</td>
<td>J/m²</td>
</tr>
</tbody>
</table>

LW, long wave; SW, short wave.
Appendix 2  Agroclimatic Atlas of Ireland

The following agro-climate datasets were prepared for the *Agroclimatic Atlas of Ireland*:

1. mean annual precipitation;
2. mean monthly precipitation;
3. number of wet days per year (varying thresholds);
4. mean daily temperatures;
5. mean monthly temperatures;
6. maximum/minimum temperatures for specific months;
7. number of frost days;
8. $\text{ET}_0$;
9. $\text{ET}_s$;
10. SMDs;
11. number of field capacity days (derived from the MÉRA dataset);
12. growing season length and start and end dates;
13. SPI (varying thresholds).

For all agro-climate variables, the current climate normal period of 1981–2010 is considered. Unless stated otherwise, all datasets were derived using the Met Éireann observed gridded rainfall and temperature datasets, with 1-km grid spacings. First, for no. 7, it should be noted that the number of days of well-drained soils at field capacity is equal to that for excessively drained soils. Second, the field capacities have been taken to be 0.1 instead of 0 for well-drained soils and –9.9 for all other soil types. This is to accommodate regions where the soils are very nearly at field capacity, allowing for $\text{SMD}=0.001$, for example, to be registered as a field capacity day. Example figures of agroclimate outputs are shown in Figures A2.1–A.2.12.
Figure A2.1. Mean daily temperature (left) and mean daily temperature range (right) for 1981–2010.

Figure A2.2. Mean January minimum temperatures in 1981–2010 (left) and mean July maximum temperatures in 1981–2010 (right).

Figure A2.3. Grass-growing season: (a) mean season start date, (b) mean season end date and (c) mean season length in days per year (1981–2010).
Figure A2.4. Mean daily temperatures for individual months (1981–2010).

Figure A2.5. Average number of frost days per year (1981–2010).

Figure A2.6. Mean annual precipitation (mm/year) from Met Éireann gridded observational datasets (1981–2010).
Figure A2.7. Mean monthly precipitation (mm/month) from Met Éireann gridded observational datasets (1981–2010).

Figure A2.8. Number of wet days at different thresholds: ≥ 1, ≥ 5, ≥ 10, ≥ 15, ≥ 20 and ≥ 30 mm (1981–2010).
Figure A2.9. SPI windows from 1981 to 2016 for Belmullet (left) and Cork Airport (right).

Figure A2.10. SPI windows from 1981 to 2016 for Casement Aerodrome (left) and Dublin Airport (right).
Figure A2.11. SPI windows from 1981 to 2016 for Malin Head (left) and Mullingar (right).

Figure A2.12. SPI windows from 1981 to 2016 for Shannon Airport (left) and Valentia Observatory (right).
Appendix 3  Accessing the Datasets

The datasets are made available through the ICHEC ERDDAP server: https://erddap.ichec.ie/erddap/files/EPA_Hydroclimate/.

The data for all models are available over the island of Ireland. At present, the data are available in netCDF format only. The files available for download are outlined in Table A3.1 and the file structure on the ERDDAP server is outlined in Figure A3.1.

An SPI time series for any location can be extracted using the cdo (climate data operators) program and a simple script whereby the user specifies a longitude and latitude location and a time interval (1–48 months). The script is provided in Figure A3.2.

Queries on the datasets and applied usage should be made to christopher.werner@ichec.ie, paul.nolan@ichec.ie or naughto@tcd.ie. Queries regarding the ERDDAP server should be directed to alastair.mckinstry@ichec.ie.

For the ETa and SMD datasets, the folder and file notations for each of the soil drainage classes are as follows:

- ED = excessively drained;
- WD = well drained;
- MD = moderately drained;
- ID = imperfectly drained;
- PD = poorly drained.

Table A3.1. List of variables available for download at ICHEC’s ERDDAP server

<table>
<thead>
<tr>
<th>File name</th>
<th>Description</th>
<th>Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Model)_(variable)-daily.nc</td>
<td>Daily dataset from 1981 to 2016</td>
<td>ETa, ETa, SMD</td>
</tr>
<tr>
<td>(Model)_(variable)-monthlysums.nc</td>
<td>Monthly sums from 1981 to 2016 (432 time steps)</td>
<td>ETa, ETa</td>
</tr>
<tr>
<td>(Model)_(variable)-monthsavg.nc</td>
<td>Average of monthly sums 1981 to 2016 (12 time steps)</td>
<td>ETa, ETa</td>
</tr>
<tr>
<td>(Model)_(variable)-seasonsum.nc</td>
<td>Seasonal sums from 1981 to 2016 (108 time steps)</td>
<td>ETa, ETa</td>
</tr>
<tr>
<td>(Model)_(variable)-seasonsumavg.nc</td>
<td>Average of seasonal sums 1981 to 2016 (4 time steps)</td>
<td>ETa, ETa</td>
</tr>
<tr>
<td>(Model)_(variable)-yearlysums.nc</td>
<td>Yearly sums from 1981 to 2016 (36 time steps)</td>
<td>ETa, ETa</td>
</tr>
<tr>
<td>(Model)_(variable)-yearlysumavg.nc</td>
<td>Average of yearly sums 1981 to 2016 (1 time step)</td>
<td>ETa, ETa</td>
</tr>
</tbody>
</table>

*Signifies data for COSMO-CLM and WRF available for 2017.

Figure A3.1. Hierarchy of files in ICHEC’s ERDDAP server.
### User Input

RCM = OBS  

lon = -7.36; lat = 53.54;  

len_month = 48

### End of User Input

```bash
cdo -s remapnn,lon=${lon}_lat=${lat} –selname,SPI_M${len_month} SPI_${RCM}_1981-2016.nc temp.nc
cdo -s infor temp.nc > a1
sed –i '/9.9692e+36/d' a1
awk '{print $1,$3,$9}' a1 > a2 && rm a1
sed 's/-/ /g' a2 > a3 && rm a2
tail –n +2 a3 > a4 && rm a3
echo “M${len_month}=[“ > top
echo “};” > end
cat top a4 end > SPI_M${len_month}_${RCM}_lat${lat}_lon${lon}.m
```

Figure A3.2. Script using cdo (climate data operators) to obtain the SPI at a user-specified location from the SPI dataset.
Tá an Ghníomhaireacht um Chaomhnú Comhshaoil Tá an Ghníomhaireacht um Chaomhnú Comhshaoil (GCC) feirgnach as an gcomhshaol a chaomhnaí agus a theafhlaí mar chúnamh na haonú na mhuintir na hÉireann. Tá aon phoist a imreachtadh do phoist mhuintir na hÉireann. Tá aon phoist a imreachtadh do phoist mhuintir na hÉireann.

Is féidir obair na Gníomhaireachta a roinnt ina tri phríomhréimeː

**Rialúː** Déanaímid córais éifeachta rialaithe agus comhlianta comhshaol a chur i bhfeidhm chun thờibh maithe comhshaol a sholáthar agus chun diriú orthu stiúcháin ná gholiom leis na córais sin.

**Eolasː** Soláthraimíd sonrai, faisnéis agus meastamhí comhshaol atá ar archaighdeán, sproicadh, tréithiú chun bona eolais a chur faoin gcinnteoir an rialaithe ag gach leibhéal.

**Tacaíochtː** Bimid ag saothrú i gcomhar na grúpaí eile chun tacú le comhshaol atá glan, tairgíúil agus cosantá go maith, agus le hiompar a chur chuidh le comhshaol inbhunaithe.

**Ár bhFreagrachtáí**

Ceadaúnú
Déanaímid na gniomhaíochtaí seo a leanas a rialú ina chomhthionscadai ina cheart.

- saoráidí drámaíola (m.sh. litéaréamh lioneal talain, loiseoirí, stáisiúin aisteoir drámaíola);
- gniomhaíochtaí tionsclaíochta ar scála móir (m.sh. deantaíocht cógaístíochta, déantaíocht stroighne, stáisiúin chumhacht);
- an diantalmhaíocht (m.sh. slua, éanlaith);
- úsáid shrianta agus scoileadh rialaithe Órgáinach Géinmhodhnaithe (OGM);
- foinsí rialaitheacht ianáíchú (m.sh. treamhán x-gha agus radaiteiripé, foinsí tionsclaíochta);
- áiseanna móra stórála peitril;
- radaiteirí pé, foinsí tionsclaíochta (m.sh. trealamh x-gha agus radaiteiripé, foinsí tionsclaíochta);
- úsáid shrianta agus scoileadh rialaithe Órgáinach Géinmhodhnaithe (OGM);
- foinsí rialaitheacht i an údarás a bhfuil ceadúnas ón nGníomhaireacht acu.

Forfheidhmiú Náisiúnta i leith Cúrsáil Comhshaol

- Cláir náisiúnta iníthchú agus círeagrácthaí a dhéanann gach bliain ar shaoráidí a bhfuil ceadaúnas ón nGníomhaireacht acu.
- Mairinseacht a dhéanamh ar fhreagrachtáí comhshaolaí a chur i gceist ná n-údarás áitiúil.
- Caighdeán an uisce ól, ama sholáthar ag soláthraithe uisce phoiblí, a mhaoirísí.
- Obair le húdaráis áitiúla agus le gníomhaíochtaí diobhálach na radachtaí agus an fhreagrachtáidh.
- Chur i bhfeidhm rialaitheacha don rialaitheacht.
- Cabhrú le pleananna náisiúnta a fhorbairt le haghaidh éigeandálaí.

Cosaint Redaíochta

- Monatóireacht a dhéanamh ar leibhéal radaíochta, measúnacht a dhéanamh ar leibhéal radaíochta, measúnacht a dhéanamh ar leibhéal radaíochta, measúnacht a dhéanamh ar leibhéal radaíochta.
- Comhairle agus treoir a chur ar fáil d'earnáil na tionsclaíochta.
- Measúnacht a dhéanamh ar thionchar pleananna agus leis an tsábháilteacht raideolaíoch.
- Sáinsírbhísí cosantá a dhéanamh ar leibhéal radaíochta, nó maoirsí a dhéanamh ar sholáthar na seirbhísí sin.

Treoir, Faisnéis Inrochtana agus Oideachas

- Comhairle agus treoir a chur a fáil d’aer ón rath a bhfuil tionsclaíochta agus an fhreagra agus a bhfuil fearr na bhfícheadtaí a bhainistiú.
- Faisnéis thráthúil ar an gcomhshaol agus don phobal náisiúnta agus na n-údarás áitiúil.
- Measúnacht a dhéanamh ar thionchar pleananna agus leis an tsábháilteacht raideolaíoch.
- Sáinsírbhísí cosantá a dhéanamh ar leibhéal radaíochta, nó maoirsí a dhéanamh ar sholáthar na seirbhísí sin.

Múscailt Feasachta agus Athrú Iompraíochta

- Feasachta chomhshaol níos fearr a ghiúntú agus d’éifeacht a chur chun feidhm i leith dhéanamh ar leibhéal radaíochta.
- Tástaí le haghaidh radóin a dhéanamh ar leibhéal radaíochta.
- Plean Náisiúnta Bainistíochta Draíocht in Éirinn.

Bainistíocht, Anáilís agus Tuairiscí ar an gComhshaoil

- Monatóireacht a dhéanamh ar chaidlocht a chaidíocht a bhainistiú.
- Tuairiscí neamhspleách le cabhrú le cinntí a chun rialaitheacht a dhéanamh.
- Tuairiscí neamhspleách le cabhrú le cinntí a chun rialaitheacht a dhéanamh.

**Measúnacht Straitéiseach Timpeallachta**

- Measúnacht a dhéanamh ar thionchar pleananna agus leis an gcomhshaol.

Bainistíocht, Anáilís agus Tuairiscí ar an gComhshaoil

- Monatóireacht a dhéanamh ar chaidlocht a chaidíocht a bhainistiú.
- Tuairiscí neamhspleách le cabhrú le cinntí a chun rialaitheacht a dhéanamh.
- Tuairiscí neamhspleách le cabhrú le cinntí a chun rialaitheacht a dhéanamh.

**Measúnacht Straitéiseach Timpeallachta**

- Measúnacht a dhéanamh ar thionchar pleananna agus leis an gcomhshaol.

Bainistíocht, Anáilís agus Tuairiscí ar an gComhshaoil

- Monatóireacht a dhéanamh ar chaidlocht a chaidíocht a bhainistiú.
- Tuairiscí neamhspleách le cabhrú le cinntí a chun rialaitheacht a dhéanamh.
- Tuairiscí neamhspleách le cabhrú le cinntí a chun rialaitheacht a dhéanamh.

**Measúnacht Straitéiseach Timpeallachta**

- Measúnacht a dhéanamh ar thionchar pleananna agus leis an gcomhshaol.
Identifying Pressures

Key stakeholders in water resource management, such as the Office of Public Works (OPW), Irish Water, the Environmental Protection Agency (EPA) and Geological Survey Ireland (GSI), share a common challenge in managing and protecting the aquatic environment, particularly in the face of climate variability, land use and demographic change, pollution and the demand for natural resources. These challenges are exacerbated by a warming climate, which is expected to result in an increase in drought and flooding events in Ireland. The EPA Research Programme specifically calls for support for development of the analysis of the fundamental processes that drive the rate and extent of climate change. Such analysis is necessary to provide the evidence base to inform relevant national policymakers, planners and stakeholders of potential climate-related mitigation strategies as called for under the National Climate Change Adaptation Framework (NCCAF). However, the datasets required for such research have not been available in Ireland.

Informing Policy

Under the Water Framework Directive (WFD), the state is responsible for protecting and maintaining groundwater bodies and catchment areas and ensuring the long-term sustainability of water resources. Hydro-climate variables such as evapotranspiration and soil moisture conditions are crucial factors in ensuring water sustainability, understanding groundwater recharge, agronomic management and the management of flood and drought. The research and datasets resulting from this project will assist Ireland to meet its obligations under EU directives such as the WFD.

The knowledge gained, and hydro-climate datasets generated, through this research will contribute towards the long-term goal of mitigating and adapting to climate change and developing a climate-resilient Ireland by 2050, as set out in the EPA Climate Research Strategy 2014–2020. To facilitate climate change policy, a greater understanding of the primary processes driving energy and water exchanges within the hydrological cycle is required for hydro-climate trend analysis and prediction. This research will inform climate change policy through the provision of long-term high-resolution datasets of key hydro-climate meteorological variables – a fundamental foundation for the interpretation of climate change trends in Irish hydro-climatology.

Developing Solutions

The research presents an important data resource for Irish researchers, policymakers and industry by providing, for the first time, high-resolution gridded datasets of hydro-climate variables. It is envisaged that the datasets will lead to a better understanding not only of the physical climate system but also of the interaction between climate and Irish society. In addition, it is envisaged that the datasets will be used as a basis for more-focused hydro-climate impact studies. To promote the use of the data and enhance climate research in Ireland, the datasets are made publicly available to researchers, policymakers, the general public and Irish industry through the Irish Centre for High-End Computing (ICHEC) ERDDAP server.

This study has produced high-resolution gridded datasets of hydro-climate variables, including:

- reference evapotranspiration;
- actual evapotranspiration (five drainage classes);
- soil moisture deficits (five drainage classes);
- Standardised Precipitation Index for various intervals.

In addition, the evapotranspiration and soil moisture deficit datasets were improved by incorporating the Teagasc Indicative Soil Drainage Map, resulting in a more accurate representation of actual soil conditions throughout the country.