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Web processing service for climate impact and extreme weather event analyses. Flyingpigeon (Version 1.0)

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Abstract

Analyses of extreme weather events and their impacts often requires big data processing of ensembles of climate model simulations. Researchers generally proceed by downloading the data from the providers and processing the data files “at home” with their own analysis processes. However, the growing amount of available climate model and observation data makes this procedure quite awkward. In addition, data processing knowledge is kept local, instead of being consolidated into a common resource of reusable code. These drawbacks can be mitigated by using a web processing service (WPS). A WPS hosts services such as data analysis processes that are accessible over the web, and can be installed close to the data archives.

We developed a WPS named ‘flyingpigeon’ that communicates over an HTTP network protocol based on standards defined by the Open Geospatial Consortium (OGC) [23], to be used by climatologists and impact modelers as a tool for analyzing large datasets remotely.

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Here, we present the current processes we developed in flyingpigeon relating to commonly-used processes (preprocessing steps, spatial subsets at continent, country or region level, and climate indices) as well as methods for specific climate data analysis (weather regimes, analogues of circulation, segetal flora distribution, and species distribution models). We also developed a novel, browser-based interactive data visualization for circulation analogues, illustrating the flexibility of WPS in designing custom outputs.

Bringing the software to the data instead of transferring the data to the code is becoming increasingly necessary, especially with the upcoming massive climate datasets.

Keywords: Web Processing Service, climate impact, extreme weather events, birdhouse, OGC

1 **Highlights:**

- 2 • A tool for remote processing of climate model data is presented
3 • Reduces the difficulties of climate model data analysis
4 • Standardized scientific methods for climate impact and extreme weather
5 events
6 • Able to communicate with other web services

7 **1. Introduction**

8 Processing of climate data is typically carried out by individual researchers,
9 who create and run their own scripts in their preferred programming lan-
10 guage, either locally or in environments internal to their institutions. Thus,
11 there is a vast but unconnected body of knowledge that is not readily avail-
12 able to the climate science community with the risk of being continually
13 replicated as researchers write scripts for processes that have already been
14 well-developed by others. Furthermore, climate data, such as the upcoming
15 Phase 6 of the Coupled Model Intercomparison Project [CMIP6](#) and the Co-
16 ordinated Regional Climate Downscaling Experiment [CORDEX](#), is becoming
17 too large to download and process locally.

18

19 Here, we present a web processing service (WPS) named 'flyingpigeon'
20 (Version 1.0) containing processes written for and by climatologists and im-
21 pact modelers for climate impact and extreme weather events analyses. These
22 users are experts in their scientific fields with a good knowledge of climate
23 model data usage, including the uncertainties associated with the data and
24 the methods implemented in the processes.

25
26 Flyingpigeon (henceforth always referring to Version 1.0) is part of the
27 open source project [birdhouse](#) (under the Apache License 2.0), a collection of
28 Open Geospatial Consortium (OGC) WPSs that provides data processing for
29 the climate science community. Like all other compartments in birdhouse,
30 flyingpigeon communicates over the web using the HTTP protocol based
31 WPS Interface Standard for geospatial processing services defined by OGC
32 [23]. A make file that handles appropriate software dependencies makes it
33 easy to install. Flyingpigeon and the processes we developed are freely avail-
34 able from the [flyingpigeon repository](#) on GitHub. To run efficiently, the code
35 should be installed on a system with appropriate resources.

36 Birdhouse evolved out of data management projects (C3Grid-INAD [19],
37 ExArch [3]), LSDMA [17]), while the processes designed for flyingpigeon were
38 developed within projects related to climate impact and extreme weather
39 events analysis ([EUCLEIA](#), [A2C2](#), [Extremoscope](#)).

40 Inter-WPS communication enables operative services for international collab-
41 orations such as the Infrastructure for the European Network of Earth System
42 Modeling ([IS-ENES](#)) and Earth System Grid Federation ([ESGF](#)), and is in
43 line with other WPS developments like [52° North](#) [2] (enabling standardized
44 deployment of geo-processes on the web), the [ZOO-Project](#) [10] (able to pro-
45 cess geospatial or non geospatial data online), [climate4impact](#), and Climate
46 Information Portal of Copernicus ([CLIPC](#) [7]).

47 The goal of this paper is to introduce flyingpigeon as a WPS for climatologists
48 and impact modelers.

49 2. WPS general description

50 A WPS is a technical solution ([WPS Concepts](#)) in which processes are
51 hosted on a server and accessed over the web (Fig. 1). These processes con-
52 form to a standardized format, ensuring that they follow the principle of
53 reusable design: they can be instantiated multiple times for different input
54 arguments or data sources, customized following the same structure to handle

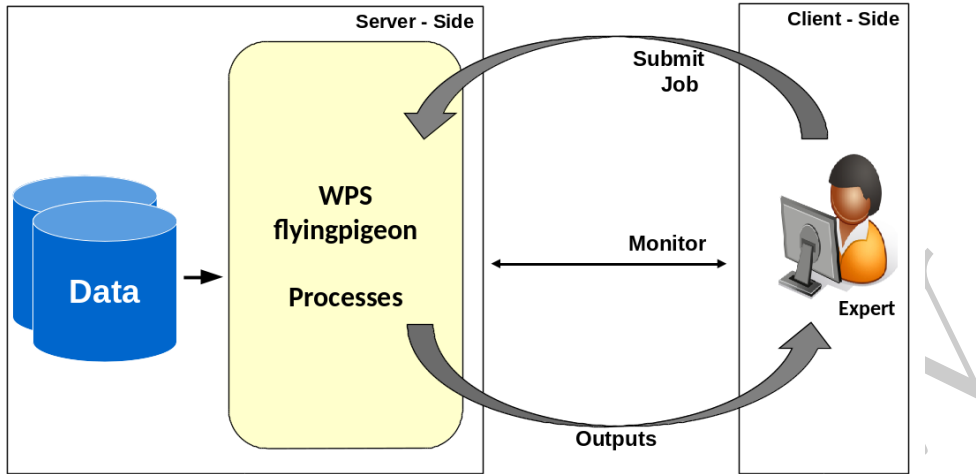


Figure 1: Schematic of WPS operations.

55 new inputs, and are modular, hence can be combined to form new processes.
 56 In addition, a WPS can be installed close to the data to enable processing
 57 directly out of the archive. A WPS can also be linked to a theoretically limit-
 58 less combination of several other WPSs, or generally OpenGIS Web Services
 59 (OWS).

60 In this paper **process** is used in the same sense as in the OGC standard: *'for*
 61 *any algorithm, calculation or model that either generates new data or trans-*
 62 *forms some input data into output data'* [23]. A submitted process is a **job**.
 63 A **service** provides a collection of processes containing scientific **methods**
 64 that focus on climate impact and extreme weather events. A combination
 65 of processes is called a **workflow**, and a collection of WPS-related software
 66 compartments is a **framework** (see Section 2).

67 WPS divides the operation into **server** and **client** side 2.2, with appropriate
 68 **security** 2.3 in between to avoid misuse.

69

70 2.1. WPS flyingpigeon

71 Flyingpigeon contains a variety of processes ranging from simple polygon
 72 subsetting to complex data analysis methods and workflows used in climate
 73 impact or extreme weather event studies (see Section 3).

74

75 One of the main software components of flyingpigeon is [OpenClimateGIS](#)
76 (OCGIS), an open source Python package designed for geospatial manipu-
77 lation, subsetting, computation, and translation of climate datasets stored
78 locally in NetCDF files or served via OPeNDAP protocols. OCGIS inter-
79 prets the climate data community’s canonical metadata standard – the [Cli-](#)
80 [mate and Forecast \(CF\) Convention](#) – maintaining standards compliance for
81 any derived CF-NetCDF output. OCGIS also supports numerous time-aware
82 computations (i.e. monthly mean, seasonal maximum), multiple output for-
83 mats (i.e. ESRI Shapefile, Comma Separated Value), and spatial interpola-
84 tion using the [Earth System Modeling Framework](#) (ESMF). OCGIS calls can
85 be executed on the whole dataset at once or divided into chunks to reduce
86 the memory load. In flyingpigeon, memory availability is checked before and
87 the call is executed accordingly.

88 Flyingpigeon is mainly written in Python but also includes processes based
89 on [CDO](#) commands, R scripts, and Fortran.

90 After submitting a job to the WPS, several data preprocessing steps are run
91 automatically. Flyingpigeon has utilities to e.g. sort files belonging to differ-
92 ent datasets, checks the variable contained in the data files, converts units,
93 rotates or unrotates grid coordinates, or generates file names based on the
94 metadata or its values.

95 An installation system simplifies the deployment of flyingpigeon on a server.
96 It is designed for Linux distributions and fetches required dependencies with
97 the [Conda](#) package management system. It uses [Buildout](#) to setup the ap-
98 plication by calling a simple install command.

99 Since the code is open source, contributions by the community are possi-
100 ble. [Online documentation](#) is generated with Sphinx [1], including [automatic](#)
101 [documentation](#) for the functions.

102 2.2. Server - Client side

103 Flyingpigeon is a server-side service embedded in the birdhouse (see Fig. 2),
104 a framework to support the development and deployment of climate data
105 processing services based on the OGC WPS standard. Flyingpigeon can be
106 run in combination with other birdhouse compartments such as **phoenix**,
107 a graphical user interface (GUI) for common web browsers that includes an
108 OGC web mapping service (WMS), or **malleefowl**, the WPS server backend
109 for data search in and fetching from the ESGF archive. Other compart-
110 ments offer processes such as quality checks for technical aspects of NetCDF
111 files ([climate forecast](#) compliance checker) or processes to execute climate

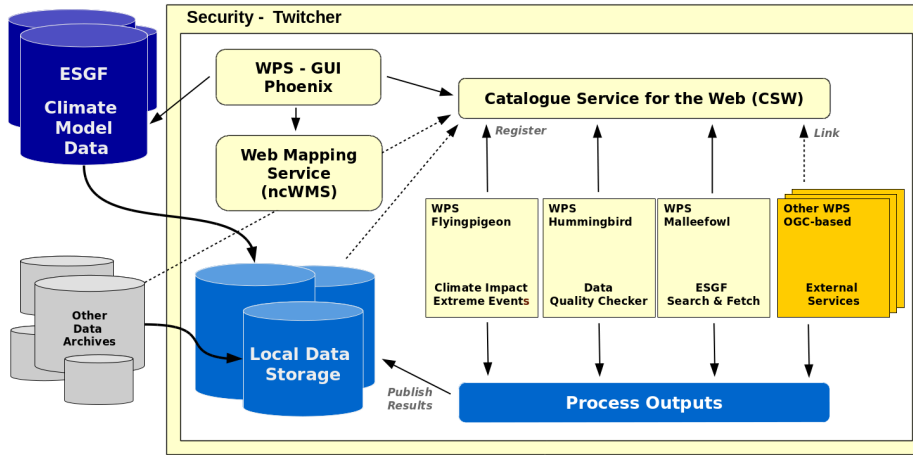


Figure 2: Main components of the birdhouse framework and connection to data archives.

112 data operations with CDO. A catalog service for the web ([CSW](#)) is used to
 113 publish results and discover available services. However, flyingpigeon is a
 114 self-contained service and can also be run operationally as a stand-alone.

115

116 On the client side, the user needs to connect to the server with an ap-
 117 propriate URL to enable communication via an HTTP protocol, which is
 118 possible in three ways:

- 119 • with a terminal command
- 120 • within a script language (e.g. Python)
- 121 • with a browser-based GUI (e.g. Phoenix)

122 Besides connecting to the server via a terminal or a script language, a job
 123 can be submitted via the Phoenix GUI, directly or through a user-friendly
 124 wizard that guides through the steps from data search to literal argument
 125 input, and finally monitors the status of the job.

126

127 *2.3. Security*

128 Web Processing Services are HTTP services and access to them can be
 129 secured by using HTTPS and firewalls. One can enable basic authentication
 130 on the HTTPS service by requiring a username and password to use the WPS
 131 service. Most WPSs are used in an internal network and their processing ca-
 132 pabilities are used by web portals. External users usually don't have direct

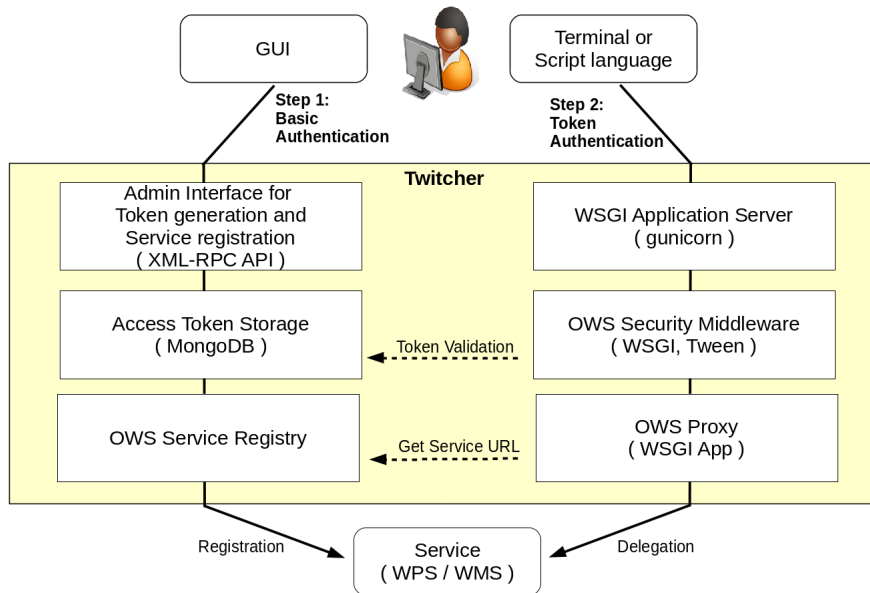


Figure 3: Twitcher security schema.

133 access to the WPS itself.

134 Birdhouse uses [Twitcher](#), a security proxy we developed for WPSs that pro-
 135 vides an easy-to-use mechanism to access WPS directly by users in a secure
 136 way. The concept is not restricted to WPS and can be extended to other
 137 services like Web Mapping Services (WMS).

138 The Twitcher security proxy protects registered WPSs and allows the execu-
 139 tion of processes over a terminal or within a script only if a valid access token
 140 is provided. A basic authentication via a GUI with username and password
 141 (Step 1 in Fig. 3) allows access to the Twitcher administration interface and
 142 triggers a token (unique string) generation. This token can be used to access
 143 the registered WPS services on the command line or in a script (Step 2 in
 144 Fig. 3). Tokens are valid only for a short period of time and can be regener-
 145 ated by repeating Step 1. Without a valid token, it is not possible to execute
 146 a process, but it is still possible to retrieve information about the service to
 147 explore provided processes and their descriptions.

148

149 The management of the access tokens and the registered WPS is controlled by the Twitcher administration interface using the [XML-RPC](#) proto-
 150

151 col (first layer in Fig. 3, left column). Access tokens are generated, validated
152 and persisted by the Access Token Storage (second layer) which uses a [MongoDB](#)
153 database. The OWS Service Registry (third layer) stores the registered
154 WPS services with the service URL and a unique service name.

155 In Step 2, the Twitcher proxy service uses a [WSGI](#) application service
156 (first layer in Fig. 3, right column), a specification for communication between
157 web servers and web applications. The OWS Security Middleware (second
158 layer) gets the provided token from the request (generated in Step 1 and
159 embedded in the URL or an HTTP header variable) and validates it using
160 the Access Token Storage. If the token is valid, the OWS Proxy (third layer)
161 retrieves the service URL for the given service name and delegates the request
162 to the registered service (WPS, WMS, etc.).

163 2.4. Input Data

164 Climate model data are commonly stored in NetCDF file format and or-
165 ganized in data archives. If data are not already stored on the WPS server,
166 they have to be fetched and stored in a structured way. Besides many other
167 datasets, the output of the CMIP5 (and upcoming CMIP6) and CORDEX
168 are stored for public access in the ESGF data archive. Birdhouse provides a
169 data search for ESGF as a search interface within the GUI or from the com-
170 mand line. A second important group of datasets are reanalyses data, which
171 are outputs from a data assimilation component of a weather forecast model.
172 In climate impact and extreme event assessment, the use of reanalyses data
173 is very common, thus some processes (see Section 3) in flyingpigeon provide a
174 preselection of reanalyses datasets and variables. By selecting an appropriate
175 variable, the data are automatically fetched within the process.
176 In the processes for analogue circulation (3.4.2) and weather regimes (3.4.1),
177 the preselection of variables are dataset subsets of the following global re-
178 analysis projects:

- 179 • *NCEP/NCAR Reanalysis 1:*
180 NCEP data [18] are available from 1948 to the present in 17 pressure
181 levels with a spatial grid resolution of $2.5^\circ \times 2.5^\circ$
- 182 • *20th Century Reanalysis version 2 (20CR):*
183 The 20CR dataset [5] is based on surface pressure observations only and
184 provides an ensemble of 56 members that contains global weather con-
185 ditions and their uncertainty from 1871–2012, available on 24 pressure
186 levels with a spatial grid resolution of $2^\circ \times 2^\circ$.

187 Local data stored on the server side can also be directly provided as input
188 data for these two processes.

189 In climate impact and extreme event assessments, some analytic methods
190 require non-climatic data. The species distribution model (SDM) process
191 (3.3.2) in flyingpigeon to predict favorability of tree species requires geograph-
192 ical coordinates of tree occurrences. A free and open access data base for
193 biodiversity data is provided by the Global Biodiversity Information Facil-
194 ity (GBIF), where observations of trees (and other species) are stored and
195 automatically fetched by the SDM process.

196 3. Processes embeded in flyingpigeon

197 Flyingpigeon is a service targeting climate researchers and experts in gen-
198 eral with a focus on climate impact models and extreme event analyses. This
199 section describes the processes that we developed so far.

200

201 3.1. Extracting spatial subsets

202 A standard operation is spatial subsetting using bounding boxes and
203 arbitrarily-sided polygons. Spatial subset operations use the OCGIS Python
204 package. Following a subset, data masks are updated on subsetted variables
205 reflecting the coordinates' spatial relationship with the subset boundary. In
206 flyingpigeon, the polygon subset process is possible at three levels of increas-
207 ing spatial resolution: continents, world countries and European administra-
208 tive regions obtained from the global administrative areas GADM database
209 (*gadm26_levels.gdb, v2.5*). To optimize subsetting performance, high reso-
210 lution GADM boundaries were simplified [42] using *mapshaper* [12] with a
211 1% point retention. The coarse resolution of target climate model inputs
212 compared with the down-sampled resolution of GADM boundaries did not
213 result in any significant data loss following a spatial subset operation. Very
214 small administrative regions were merged on the country level.

215 An additional mosaic option merges multiple polygons; otherwise, a separate
216 output file is created for each polygon. This increases the flexibility to meet
217 specific user needs. The outputs are provided as NetCDF files wrapped in a
218 tar archive.

219 In addition to polygons, a process is also available to extract longitude and
220 latitude points. Point subset data products are returned in text files con-

221 taining a timeseries table for each longitude and latitude point.

222

223 3.2. Computation of climate indices

224 Climate indices are metrics to describe climate conditions and can be
225 used to assess changes in climate over time (see the use case below), or as
226 forcing data for complex impact models (e.g. the species distribution model
227 3.3.2). Climate indices can be user-defined, but there is also a standardized
228 set provided by the [European Climate Assessment & Dataset](#) website.

229

230 The climate indices are calculated based on a time aggregation (e.g. year,
231 month, season) and include world countries polygon subsetting as an optional
232 feature. The processes fall into four categories (the last two are still under
233 development):

234

- 235 1. standard
- 236 2. percentile-based
- 237 3. multi-variable indices
- 238 4. user-defined

239 Standard indices are based on one daily input variable (near surface tem-
240 perature, precipitation). The provided indices are related to the [ICCLIM](#)
241 python package deployed in OCGIS. In the percentile-based process, a per-
242 centile is calculated over a user defined reference period. The process outputs
243 the number of days that exceed or fall below this calculated threshold (for
244 percentiles > 50 or < 50 , respectively). When deployed, the multi-variable
245 index process will allow users to specify a combination of indices. User-
246 defined indices, also under development, will allow custom index calculations
247 for single or multiple variables.

248

249 *Use case: Extremoscope.* We built an [interactive data visualization](#) to show
250 the evolution of 10 extreme climate indices in the 13 regions of France under
251 two climate scenarios (RCP 4.5 and 8.5) as part of the [Extremoscope](#) project.
252 Flyingpigeon was used to calculate the climate indices using 7 climate pro-
253 jection models for five time aggregates (four seasons and yearly).

254 The visualization displays the probability of extreme seasons or years oc-
255 ccurring, defined as exceeding the 90th/95th percentile, or falling below the

256 5th/10th percentile, based on a reference period between 1972–2100. The
257 data is filterable by each dimension (region, time aggregate, index, scenario,
258 percentile, model and year) with different charts that are linked (crossfiltered)
259 using the [crossfiltering library](#) in [dc.js](#), the Dimensional Charting JavaScript
260 library, to allow the effects of each dimension to be observed and compared.
261

262 3.3. *Climate impact related processes*

263 One main target user group of the flyingpigeon is the climate impact
264 community. In this section, the currently embedded processes for general or
265 specific climate impact studies are presented. More processes like population
266 dynamics for *anopheles gambia*, the vector transmitting *Plasmodium falciparum*
267 to assess risks of malaria infection are under development and will be
268 implemented in upcoming versions.

269 3.3.1. *Segetal flora*

270 'Segetal flora' is a term used for weeds growing in crop fields. The major-
271 ity of segetal flora species have very positive and important ecological effects
272 as a source of pollen or nectar for several insects or as nutrition for birds [16].
273 Based on field monitoring, a relation between the number of different species
274 occurring in crop fields and the annual mean temperature can be shown.
275 The relations are investigated separately for seven segetal flora groups (e.g.
276 Mediterranean or Nordic groups) and three land use types (conventional and
277 ecological land use, and one–two year self-greened fallow land). The species
278 number to mean annual temperature relations are expressed as regression
279 functions [15, 14], which are the core of the segetal flora process. With tem-
280 perature at 2m height (tas) as input data, and arguments to select segetal
281 flora type and land use, the number of species is predicted. A polygon subset
282 for a specified country can be selected with an optional argument.
283 The process returns a tar file containing NetCDF files with the appropriate
284 number of segetal flora species per grid point for each input dataset. The
285 calculation is only relevant for areas with agricultural land use.
286

287 3.3.2. *Species distribution model*

288 Species distribution models (SDMs) are numerical tools to describe the
289 relation between the distribution of a species and the environmental con-
290 ditions that are thought to lead to this distribution [11, 24]. Models are

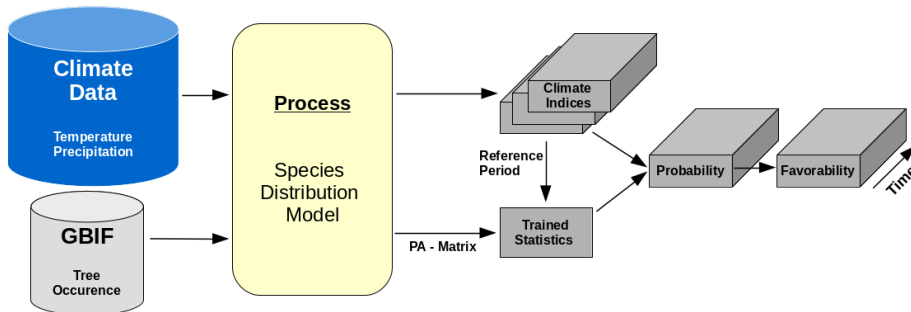


Figure 4: Schema of the Species Distribution Model process.

291 used to gain ecological insights and predict distributions across landscapes,
 292 sometimes requiring extrapolation in space and time, e.g. for climate change
 293 impact modeling (modified from [8]).

294 We implemented a SDM process that relates the distribution of tree species to
 295 climate conditions to analyze the impacts of climate change [9]. The method
 296 focuses on tree species where the distribution is independent of non-climate
 297 factors like soil or specific site conditions. We hypothesize that the climate
 298 conditions which limit the tree species distribution (e.g. heat, precipitation,
 299 winter temperatures, drought [21]) can be described with climate indices (de-
 300 fined in section 3.2).

301 Fig. 4 shows the schematic workflow of the SDM process. Climate indices are
 302 calculated based on climate model variables (daily temperature and precipi-
 303 tation values). Tree species data can be fetched from the global biodiversity
 304 information facility (GBIF) database and fed to the SDM process. The
 305 geographical coordinates of the tree occurrence are then translated into a
 306 presence-absence (PA) matrix with the grid size of the input climate model
 307 data. Ocean and large lake areas are excluded in the PA matrix.

308 Statistical training [36, 35] is performed based on the calculated climate
 309 indices as a mean over a reference period and the PA matrix using general-
 310 ized additive models (GAMs)[33, 37]. GAMs are flexible regression models
 311 with non-parametric (smooth) additive components [34].

312 After the statistical training, the probability of occurrence is predicted over
 313 the entire time series and transformed into a favorability [25] to compare
 314 different models. The SDM process can used with different climate indices,
 315 tree species, training performance values, and climate model datasets.

316

317 *3.4. Extreme weather events related processes*

318 Besides climate impact studies, the WPS flyingigeon also focuses on ex-
319 treme weather events investigations. This section contains examples of more
320 complex processes to calculate weather regimes (3.4.1) or analogues of circu-
321 lation (3.4.2).

322 *3.4.1. Weather regimes*

323 Weather regimes are recurring states of the atmosphere and provide a use-
324 ful description of atmospheric variability [22, 6, 30]. In extreme event studies,
325 for instance, it is possible to associate some specific seasonal weather regimes
326 with the extremes of surface variables (precipitation or temperature) by an-
327 alyzing which regime is prevailing when an extreme is encountered [40].

328 Following the methods of [22] and [39], the weather regime process computes
329 a given number of regimes (the κ value, by default $\kappa = 4$ [22]) for a region
330 (by default the North Atlantic region [80°W - 50°E , 20°N - 70°N]) using
331 values of sea level pressure (SLP) or geopotential height ($Z_g(h)$) anomalies
332 of a given season.

333 The weather regimes are computed with a k-mean classification algorithm
334 [13] on the first 10 principal components (PCs) of the SLP or geopotential
335 height ($Z_g(h)$) fields. The PCs are computed from a Empirical Orthogonal
336 Function decomposition [32] of the field. The data are weighted by the square
337 root of the cosine of the latitude to account for grid cell surface variations.
338 The obtained PCs are then classified onto κ clusters. The weather regimes
339 can be computed on a reference data set (e.g. reanalyses data). Then, other
340 datasets (e.g. climate model data) can be classified according to these refer-
341 ence weather regimes.

342 Fig. 5 shows the output for a use case where weather regimes in winter

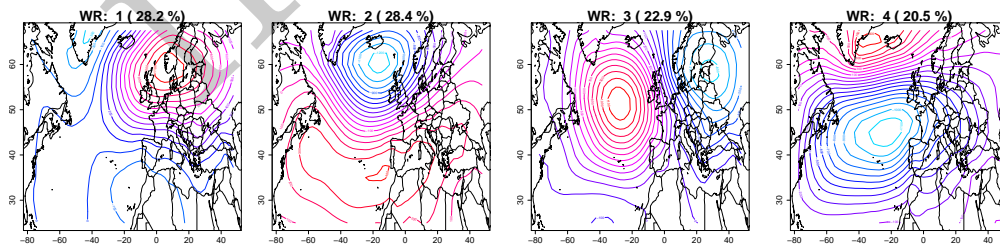


Figure 5: Weather regimes (WR) for winter months (DJF) based on NCEP sea surface pressure data (1970–2010).

Table 1: Percentual occurrence of weather regimes in winter months (DJF) trained on NCEP sea surface pressure data projected on a CMIP5 global dataset.

Year	WR 1	WR 2	WR 3	WR 4
...				
2084	35.16	28.57	30.77	5.49
2085	33.33	24.44	36.67	5.56
2086	21.11	28.89	40.00	10.00
2087	37.78	11.11	10.00	41.11
2088	18.68	19.78	37.36	24.17
2089	34.44	44.44	17.78	3.33
...				

343 months were calculated based on NCEP sea surface pressure data over a re-
 344 gion in the North Atlantic for $\kappa = 4$. The process also output an R workspace
 345 containing the statistical training values as well as a text file with the PCs
 346 and the NetCDF file with the normalized pressure values. These outputs can
 347 be used for manual postprocessing or for the weather regime projection pro-
 348 cess which calculates the percentage of each given weather regime in every
 349 year. Such a projection was done in this example for a CMIP5 dataset and
 350 Table 1 shows the calculated values.

351 3.4.2. Analogues of circulation

352 Analogues of circulation provide a versatile tool to investigate the rela-
 353 tion between climate variables (such as temperature or precipitation) and
 354 large-scale atmospheric circulation patterns (SLP or $Z_g(\text{h})$).
 355 For an SLP/ $Z_g(\text{h})$ pattern on a given day, the idea is to select days that have
 356 a calendar proximity (i.e. within a time window around the given date in
 357 all years except the year of the given day) and that minimize a distance be-
 358 tween the circulation patterns. This approach has been used to infer climate
 359 reconstructions from SLP fields [26, 41], in weather forecast predictability as-
 360 sessment [20], downscaling of climate variables [43, 29], detection/attribution
 361 studies [31, 27, 4] and stochastic weather generators [38].

362

363 *Analogues detection process.* The analogues from this flyingpigeon process
 364 are mainly used to study the conditional attribution of extreme events to dy-
 365 namics, thus describing only the thermodynamic changes in weather events.

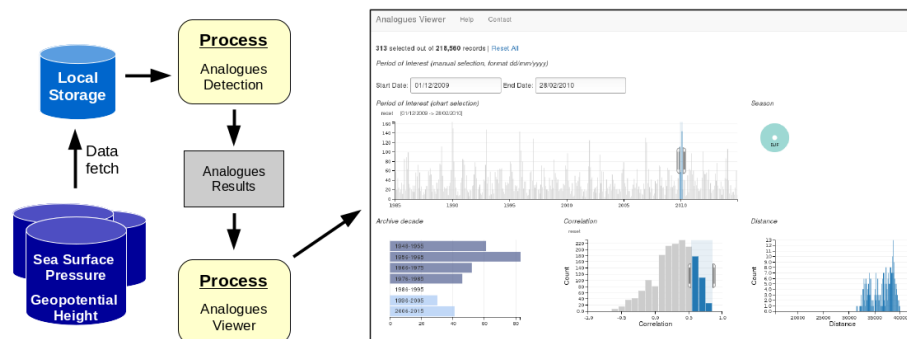


Figure 6: Schema of the analogues workflow.

366 For a given continuous extreme event period (e.g. an extreme monthly tem-
 367 perature), the process seeks in past archives flows similar to those in the
 368 continuous period and reconstructs a monthly temperature from these past
 369 flow analogue days. The resulting temperature is then compared to the cur-
 370 rent one, providing an estimate of thermodynamic changes.

371 The process uses a circulation analogue simulation FORTRAN code ([CASTf90](#))
 372 to compute analogues of circulation. The user can choose a time period for
 373 which daily analogues are computed and an archive period, that is, the time
 374 period to resample from. The user can also select a distance (Euclidean,
 375 Mahalanobis, correlation, Teweles-Wobus S1 [28], how many analogues per
 376 day to retain, a rectangular region (in longitude–latitude), whether to work
 377 with anomalies or not and some more options like the output file format.
 378 The result is a list of analogue dates for each simulation day and the corre-
 379 sponding distance values.

380

381 *Analogues viewer process.* To explore the properties of the analogues detec-
 382 tion process, we developed an analogues viewer process that produces an
 383 interactive data visualization output as an HTML page hosted on the server-
 384 side. This viewer uses [dc.js](#), the Dimensional Charting JavaScript library
 385 and a [crossfiltering library](#) to produce interactive charts that can be filtered
 386 based on data parameters. For each filter selection, all charts are simultane-
 387 ously updated (crossfiltered).

388 Figure 6 shows a schematic of the analogues workflow with a screenshot of
 389 the visualisation. For this example, the winter of 2010 was selected in the
 390 bar plot, which filtered all charts to display counts of only those analogues

391 pertaining to this time period. The display was further filtered by selecting
392 analogues with correlation coefficients > 0.5 . The decadal distribution of
393 analogues and changes across time can be immediately seen by sliding the
394 time window.

395 The analogues viewer demonstrates two powerful advantages of using WPS
396 for data analysis: 1) it is straight-forward to 'chain' processes together so
397 that the output of one process can be used as the input of another, allowing
398 data analysis to be re-imagined as a workflow, and 2) processes can be com-
399 pletely custom-designed. Here, we integrate data visualization capability –
400 normally a step performed in an environment completely separate from the
401 analysis and requiring a specialized skill that is often not within the scope
402 of the scientific researcher – directly into flyingpigeon, accessible simply by
403 launching the output HTML link.

405 **4. Conclusion**

406 Flyingpigeon, as a compartment of birdhouse, is an advanced toolbox
407 that can be used to process the increasingly large amount of climate model
408 data in a standardized and secure way. This current version is an initial se-
409 lection of processes commonly used for climate impact and extreme weather
410 event analysis. Flyingpigeon, connected to other OWSs, has access to various
411 convenient features such as ESGF data search, visualisation via the WMS,
412 and catalogue services. It allows collaborative data and methods sharing
413 and access to several data archives. Process outputs can be recycled in other
414 processes in a workflow. All these advantages are possible regardless of the
415 script language of the methods.

416 The transparency of the source code as an open source project enables quick
417 and easy exchange of developer knowledge, good quality control and frequent
418 updates of the analysis methods and performance improvements.

419 Flyingpigeon reduces the difficulty of data processing and is a solution to
420 facilitate the daily work for the climate community.

422 **5. Outlook**

423 The increasing number of developers and users ensures further improv-
424 ment of features, documentation, guidelines and tutorials. Currently, high-
425 performance computing providers located close to the data archives are being

426 established in the climate community to keep up with the demand for WPS.
427

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434
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