# **Guidance framework to apply** 1 <sup>2</sup> good practicebest practices in ecological data analysis: Lessons 3 learned from building Galaxy-4 Ecology 5

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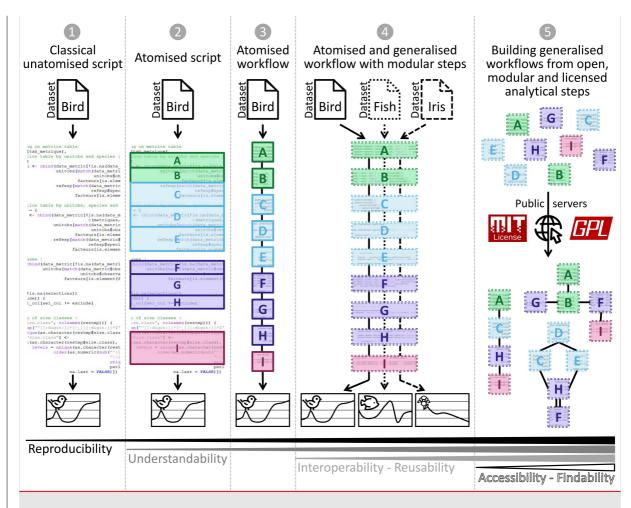
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### 71 **ABSTRACT**

Numerous conceptual frameworks exist for good practicebest practices in 72 research data and analysis (e.g. Open Science and FAIR principles). In 73 practice, there is a need for further progress to improve transparency, 74 reproducibility, and confidence in ecology. Here, we propose a practical 75 and operational framework for researchers and experts in ecology to 76 achieve good practicebest practices for building analytical procedures 77 from individual research projects to production-level analytical pipelines-78 based on atomisation and generalisation. We introduce the concept of 79 atomisation-\_to identify analytical steps which support generalisation by 80 81 allowing us to go beyond single analyses. The term atomisation is employed to convey the idea of single analytical steps as "atoms" 82 composing an analytical procedure. When generalised, "atoms" can be 83 used in more than a single case analysis. These guidelines were 84 established during the development of the Galaxy-Ecology initiative, a 85 web platform dedicated to data analysis in ecology. Galaxy-Ecology allows 86 us to demonstrate a way to reach higher levels of reproducibility in 87 ecological sciences by increasing the accessibility and reusability of 88 analytical workflows once atomised and generalised. 89

**Graphical abstract** – Levels of attainable good practicebest practices through the atomisation – generalisation framework



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*Keywords:* Biodiversity; Reproducible analyses; Galaxy; Good practiceBest
 practices; Atomisation; Generalisation; Workflows; Ecoinformatics; Conda;

96 Container; Common Workflow Language; RO-CRATE

### Introduction

98 Ecology's Reproducibility Crisis

Research in ecology is increasingly shaped by the availability of novel 99 analytical solutions and statistical tools. Given the ever-growing amount of 100 data available, much attention is often given to the thought process behind 101 102 statistical analyses to handle different data distributions, pseudo-replication, and sampling biases for instance (NERC 2010, 2012; Hampton et al., 2017; 103 Emery et al., 2021). Despite the high-quality standards required by the 104 scientific community from data access to analysis, the level of complexity of 105 ecological systems makes results difficult to reproduce. The ongoing 106 "reproducibility crisis" has also led researchers to pay closer attention to the 107 108 quality of analyses to increase confidence in their studies and conclusions 109 (Ioannidis, 2022; Fanelli, 2018).

Reproducibility (i.e. different teams and experimental setups obtaining 110 similar results; Plesser, 2018) is one of the main criteria for evaluating robust 111 science and reliable conclusions. The term "reproducibility" is a relative 112 concept and has known various definitions depending on field and context. 113 Reproducibility of analyses In ecological sciences, most in-situ observations-114 are not strictly reproducible due to stochasticity. Accordingly, the focus has 115 116 been directed towards the reproducibility of analyses ("computational reproducibility") is defined by Cohen-Boulakia et al. (2017) as the ability of 117 distinct analyses to reach to the same conclusion. over the reproducibility of 118 data collection (Powers & Hampton, 2019; Samota & Davey, 2021). 119 Reproducibility can be achieved at different levels of the analytical workflow, 120 from primary data access to results. Archmiller et al., 2020 and Minocher et-121 al., 2021 tried to evaluate computational reproducibility in 74 studies in-122 123 wildlife science and 560 studies in biological and behavioural sciences. Although these authors found high rates of computational reproducibility 124 when data and analytical procedures could be fully retrieved, they 125 encountered significant difficulty in retrieving the data files and analytical 126 procedures in most studies. 127

Given the high complexity and the massive amount of information 128 required to retrieve results using a broad range of data and methods, 129 130 achieving sufficient reproducibility must be facilitated. In addition, researchers are increasingly challenged to stay up-to-date with the ever-131 growing number of advanced methods and technologies for data acquisition, 132 storage, and analysis (Hampton et al., 2017). Providing technical and 133 practical support to reduce the perceived complexity of analytical workflows-134 could increase and accelerate the diffusion of good practices in the research 135 community, fostering understanding for a wider audience thereby facilitating 136 transparency and improving reproducibility. Here, we explore how 137 computational reproducibility can be easily implemented in ecological 138 sciences using simple and practical guidelines. 139

140 In the current context of the global biodiversity crisis, the scientific 141 community needs to use all available data and provide as robust as possible 142 evidence regarding the state and dynamic of ecological systems, from 143 genetic to ecosystem. At the same time, using analytical tools to provide

robust evidence can be complex and may require advanced skills that are not
widely available across the scientific community (Hampton *et al.*, 2017).
Therefore, operational solutions and methodological guidelines can allow the
analytical workflows to be more accessible without degrading the scientific
quality of the analyseis, and thus, promote efficient and broad deployment of
good practicebest practices.

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Is the ecology community failing to meet good practicebest practices?

The first step towards reproducibility is knowing current good practicebest 151 practices and recommendations. Among them, the FAIR principles (Wilkinson 152 et al., 2016), for which the availability of the data and the code used for each 153 published result is an essential criterion, may be key for appropriate 154 management through the data life cycle (Michener, 2015). The FAIR 155 principles (see also CARE principles by Carroll et al., 2020) are considered as 156 a founding framework to share data along four important elements: 157 "Findable" for humans and machines; "Accessible" with a detailed access 158 procedure; "Interoperable" for interaction with other data or applications; 159 "Reusable" in an identical or different context. In addition to these principles, 160 propositions have been delimited within several thematic communities in 161 162 ecology to evaluate and enhance best practices application, notably the 163 Species Distribution Modelling communities (Araújo et al., 2019; Zurell et al., 2020). 164

In 2022, Gomes and collaborators identified 12 barriers to data and code
sharing, ranging from unclarity of processes to fear of inappropriate use and
insecurities around data and code quality (Gomes *et al.*, 2022). Although data
accessibility has been substantially improved in ecology during the past
decade, sharing analytical scripts and codes remain largely marginal (IvimeyCook *et al.*, 2023Archmiller *et al.*, 2020; ). According to Culina *et al.*, 2020;
Minocher *et al.*, 2021; Ivimey-Cook *et al.*, 2023).<sub>7</sub>

in a "random sample of 346 nonmolecular articles published between
 2015 and 2019", 79% had data availability but only 27% had code availability
 despite a tendency for journals to encourage code sharing (75% of assessed
 ecological journals).

176 Low code availability compared to data availability may suggest a lack of 177 technical solutions for sharing computing codes. Nevertheless, manyrepositories dedicated to sharing code exist, such as GitHub 178 (https://github.org), which software developers widely use to collaborate and 179 share codes publicly and privately. Besides, the Software Heritage initiative 180 automatically archives all openly available code from GitHub, ensuring long-181 term preservation (https://archiveprogram.github.com; Di Cosmo & Zacchiroli, 182 2017). Alternatively, other solutions for data archiving may be used, even if 183 not explicitly focused on code sharing (e.g., Zenodo, national public 184 repositories; see also TRUST principles for data repositories, Lin et al., 2020). 185

However, even if long-term public archiving ofsharing code is necessary to
 achieve good computational reproducibility, it is insufficient. Therefore, many guidelines and principles have been developed in the recent years. Among others, the utilisation of computational workflows has been suggested as a
 solution for improving computational reproducibility (Cohen-Boulakia *et al.*,

2017; Grüning et al., 2018) through software such as Snakemake (Köster & 191 Rahmann, 2012), Nextflow (Di Tommaso et al., 2017), or Galaxy (The Galaxy 192 Community, 2022). A workflow is generally defined as a sequence of distinct 193 computational tasks for a particular objective (Goble et al., 2020). As such, a 194 195 workflow represents the backbone of a single specific analysis. Throughout the analytical procedure, a typical workflow starts with raw data, which can 196 be extracted from several databases or data files and processed through a 197 series of analytical steps. The products resulting from these analytical steps 198 (*i.e.* the outputs of the computational workflow) can be data files, graphic 199 representations and any associated metrics. In this respect, computer code 200 can also be considered as research data (Borgman, 2020). 201

- When properly designed, a certain level of reproducibility can be easily achieved since workflow languages naturally capture the following four key elements (Cohen-Boulakia *et al.*, 2017):
- 205 the specificities of the workflow, the analysis steps and associated
   206 tools;
- 207 the workflow entries, datasets and parameters;
- 208 the environment and context of the use of the workflow;
- 209 the results obtained and the outputs of the workflow.

210 In the original publication of Wilkinson et al. (2016), the focus of FAIR principles was mainly on <u>observational</u> data. However, the principles can be 211 applied to software and computational workflows (Lamprecht et al., 2019; 212 Goble et al., 2020). For instance, a code shared as supplementary material of 213 a non-open access publication could be considered as "Interoperable" but is 214 not easily "Findable", "Accessible", or "Reusable". In contrast, a large block of 215 code consisting of several hundred lines, from data pre-processing to final 216 217 results and graphics as pictured in the Graphical abstract **0**, may require 218 efforts to understand and adapt to other kinds of data ("non-reusable"), mainly if annotations or comments are limited. Similarly, an analytical 219 procedure shared without indicating the versions of hardware, software, and 220 packages has a low chance of producing identical outputs, making it non-less 221 reproducible. These issues may harm the scientific community by preventing 222 fully transparent communication among users about knowledge production 223 and practice comparison. They can also be detrimental to individual authors, 224 225 when they need to update or run new analyses.

226 Impact on Ecology Research

The efficiency of the expertise and research is greatly affected by the lack 227 of computational reproducibility and FAIRness of analytical procedures. FAIR 228 research data was estimated to save 10.2 billion € per year in Europe 229 (Munafò et al., 2017; European commission, 20189; Gomes et al., 2022). 230 Indeed, analyses and underlying conclusions cannot have a tangible impact if 231 the raw data, the analytical procedures, and the outputs resulting from these 232 procedures are not easily findable, accessible, interoperable and reusable. 233 Moreover, consistent application of reproducibility and FAIR principles will 234 improve trust in research studies and scientific reports (Powers & Hampton, 235 236 2019; Lortie, 2021; Jenkins et al., 2023).

237 The widespread use of computational languages to process large-scale data and analyse complex systems has been a major advance in studying the 238 ecosphere at any spatio-temporal scale (Michener & Jones, 2012; Farley et al., 239 2018). Even if computational capacity may represent a significant limitation 240 for analysing large data files or using resource-intensive algorithms (Green & 241 Figuerola, 2005), computation clusters nowadays exist to overcome such-242 challenges (Hampton et al., 2017; Larcombe et al., 2017). However, the ever-243 growing technical and programming skills required to take advantage of such 244 computational solutions by the scientific community raise new challenges 245 (Jetz et al., 2019; Leroy, 2022; Boyd et al., 2023). The use of increasingly 246 analytical solutions, paired with different 247 complex approaches or programming languages, mechanically reduces the number of potential users, 248 limiting collaboration and fragilising fundamental pillars of scientific 249 knowledge such as the peer-review process and critical evaluation. As a 250 response to this situation, adequate training was identified by life science 251 researchers (Community Survey Report, 2013; Williams & Teal, 2017; 252 Larcombe et al., 2017), as it would help involve more people in the 253 understanding of current analytical solutions and benefit to scientific 254 cooperation (Touchon & McCoy, 2016; Gownaris et al., 2022). Research is 255 typically structured through a highly competitive organisation, with a 256 potentially detrimental effect on scientific knowledge (Fang & Casadevall, 257 2015). Instead, fostering collaboration and collective intelligence by 258 promoting transparent sharing of analytical procedures, would offer more 259 persitent and robust ways to achieve actionable science (Ellemers, 2021). 260 Such efforts would be of paramount importance in environmental sciences 261 and the conservation of biodiversity by providing governance and guiding 262 actions with increasingly robust evidence (Keenan et al., 2012). 263

### 264 Are there simple and ready-to-use solutions?

In this note, we aim to promote the reuse of existing concepts and 265 solutions as pillars toward better practices for ecological analyses by 266 providing а streamlined framework. We believe the atomisation-267 generalisation framework presented in the second part of this note 268 represents an operational and actionable path for researchers and experts to 269 270 attain levels of good practicebest practices (e.g. reproducibility, FAIR, open science, R compendium; Casajus N., 2023) with no more investment than 271 they are able or willing to provide (Field et al., 2014). Atomisation is used to 272 refer to the identification of single analytical steps constituting an analytical 273 procedure. It is a non-standard term introduced in this note to convey the 274 idea of analytical "atoms". As for atom particles that etymologically 275 correspond to "indivisible" but are composed of subatomic particles, an 276 analytical atom represents a single analytical step composed of several 277 functions. Generalisation involves the alteration of an analytical step to 278 enlarge its applicability in diverse contexts and for diverse purposes. 279

This framework has been formalised while building the Galaxy-Ecology (Galaxy-E) initiative (see section III). Galaxy (The Galaxy Community, 2022) is a workflow-oriented web platform for sharing and processing research data. It allows <u>scientists to shareing</u>, developing, and us<u>eing</u> various datasets and

data processing tools (e.g. data formatting, statistical tests, graphic 284 representations). Many scientific workflow management systems, such as 285 Snakemake and Nextflow, operate from the command line. In ecology, 286 numerous initiatives have tried to introduce such systems, starting with more 287 user-friendly solutions. For example, the KNIME and Kepler systems with the 288 289 CoESRA initiative (Collaborative Environment for Scholarly Research and Analysis) in Australia, or Taverna with the BioVeL initiative (Biodiversity-290 Virtual e-Laboratory) in Europe. These systems are more accessible to new 291 users by offering a graphical interface while achieving high specificity 292 (Berthold et al., 2007; Hardisty et al., 2016). However, good computer-293 programming or scientific workflow management knowledge is still necessary 294 295 to use these applications correctly.

Galaxy is ready to use and has proved its efficiency and suitability in other-296 research fields, including genomics and climate science (Knijn et al. 2020; 297 Serrano-Solano et al., 2022). From a user's point of view, it offers extensive 298 computing power and a graphical interface to use analysis workflows, even-299 without experience in software development. Web-based access allows easy 300 sharing of analytical workflows between collaborators and with a broader 301 audience. Galaxy supports tools in almost any computational language, 302 including R and Python, two of the most used languages in ecology, with 303 many packages dedicated to ecological and biodiversity-oriented analyses 304 incorporated (Lai et al., 2019). 305

Galaxy enables good reproducibility for data exploration and analyses, 306 helps compute intricate analyses on big data files, enables collaboration, and 307 can support the teaching process. Galaxy-E is a Galaxy server dedicated to 308 ecological analyses maintained by the European Galaxy team (supported by 309 the German Federal Ministry of Education and Research and the German 310 Bioinformatics Infrastructure), 311 Network for and is available at 312 https://ecology.usegalaxy.eu.

Galaxy-E is a demonstration platform for applying <u>good practicebest</u> practices such as the FAIR principles and computational reproducibility for analytical procedures in ecology. Hence, this technical note is partly Galaxyoriented, not to present the platform as a prescriptive solution but to give an operational example of the <u>good practicebest practice</u>s it helps to achieve. <u>Recommendations described in this note regarding the construction of an</u> analytical procedure on Galaxy are meant to be transposable to local code

320 development or another consistent workflow engine.

321

# Framework towards good practicebest practices

## 322 Atomisation: what is it and why?

Atomisation <u>refers tois</u> dividing an analytical procedure into several specific steps ("atoms"; <u>Graphical abstract</u> **2**) generating a suite of elementary analytical steps <u>as pictured in the Graphical abstract</u> **5**. Breaking down the analytical process into atoms functioning as building blocks allows for better understanding, modularity, and visibility of the analytical flow. It permits making it more accessible to a broader audience or facilitating the peer-review process. Indeed, an extended one-block code that imports raw data, makes pre-processing steps (*e.g.* filter, formatting), conducts analyses
 (*e.g.* distribution study, modelling), and performs final representations of
 results (*e.g.* maps, plots) can be challenging to understand and reuse by
 others or even the same person after some time.

McIntire et al. (2022) described the PERFICT approach (Prediction, 334 Evaluation, Reusability, Free access, Interoperability, Continuous workflows, 335 and routine Tests) to set a new foundation for models in predictive ecology. 336 This can be applied more generally to the analytical procedure in ecology and 337 biodiversity. In their article, McIntire and collaborators make an analogy 338 between code development and Lego® construction, similar to our definition 339 of atomisation. Functions are a workflow's most fundamental analytical steps 340 and can be seen as modular pieces, alike single pieces of Lego®. Modules 341 can be created from a single or series of successive functions comparably as 342 in Lego® structures made of several pieces (e.g. meant to build cars, houses, 343 or road). These modules (or atoms, tools) can be used as standalone or 344 combined to make simple to complex analytical workflows such as (e.g. data 345 formatting or curation, running statistical models, or generating graphical 346 elements for visualisation). Doing so, the atomisation approach may facilitate 347 sharing or teaching analytical practices since beginners can easily 348 understand the general organisation of the analytical procedure by simply 349 reading the list of steps in the analysis with a limited degree of complexity. 350 Decoupling programming skills from analytical skills can make data 351 processing more accessible to a wider audience. Indeed, once each 352 elementary step is clearly identified and delimited along the atomisation 353 process, it is easier to grasp the whole analytical procedure and focus on the 354 review of each step at a time or (re)use it. New workflows can further be 355 generated by recombining existing, validated or peer-reviewed elementary 356 steps in innovative ways. This process can save time, increase confidence, 357 and avoid potential programming mistakes, allowing greater focus on 358 understanding the analytical workflow. 359

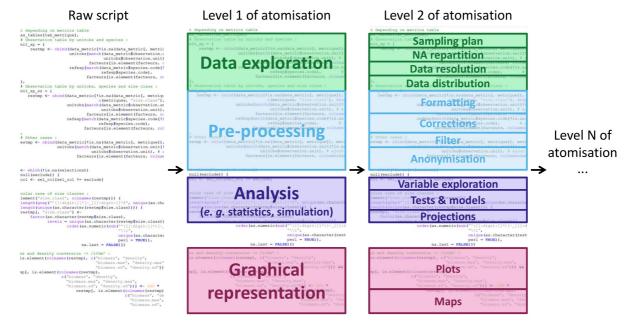
360 Generalisation: what is it and why?

Generalisation is refers to the modification of an analytical procedure to 361 make it applicable to many settings, by removing specificities related to a 362 363 particular data file or data format. Generalisation aims to optimise the reusability at different times (e.g. regular result update), enlarge the 364 application of a given analysis to different input data files while keeping the 365 initial analytical procedure fully reproducible as pictured in the Graphical 366 abstract **4**. Generalising an analytical step requires identifying key steps and 367 invariant parameters from those that must be adaptable to allow for the 368 analysis to be applied to specific characteristics of various datasets. These 369 parameters must be implemented to be easily modified if needed. 370 Generalisation can be tricky because the higher the flexibility of an analytical 371 step, the greater the risk of errors in its use. This is why generalisation should 372 be complemented by clear statement and an implementation of red flags and 373 warnings to prevent such events. As with atomisation, generalisation is 374 primarily a conceptual way to build analytical procedures. It requires minor 375

change of practices to reach certain degree of generalisation, avoiding
 additional effort later on for reusability, reproducibility, and share.

How to do atomisation and generalisation with computer codes: Findingbalance

Breaking down codes into elementary steps to achieve atomisation is not 380 381 an intuitive task <u>aet</u> first as it may target a single function or a more intricate set of several functions. There could be different degrees of atomisation, 382 depending on the grain required to decompose the analytical process (fig. 1; 383 tab. 1). The application of general guidelines and good practicebest practices 384 implies finding a balance between the most appropriate degree of 385 atomisation and generalisation. This depends on the type of analytical 386 procedure or the targeted audience (e.g. with different interests and 387 programming skills). Attention to this balance is critical to ensure that the 388 analytical procedures could be reused. For instance, a workflow in which each 389 function would be considered as a unique elementary step would optimise 390 the flexibility but may likely add unnecessary complexity. At the other 391 extreme, considering a whole analytical workflow as an elementary step may 392 make it ready-to-use and simplify its application, but would be too coarse and 393 394 therefore limit flexibility by violating the principle of atomisation.





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Figure 1 - Illustration of the atomisation of an existing code

### Table 1 Example of atomisation levels

Level 1 - big shape	Level 2	Level 3
Data exploration	Sampling plan	Complete
		Balanced
	Missing values	Proportion
		Distribution
	Data granularity	Geographic resolution
		Temporal resolution
		Measure resolution
	Data distribution	Geographic coverage
		Temporal coverage
		Measures ranges
		Summaries
Pre-processing	 Formatting	 Change file format
Pre-processing Formatting Corrections Filtering Anonymisation	Change general format	
	Corrections	Remove special characters
	001100110	Remove low trust observations
		Correct measures
	Filtering	Remove unwanted observations
	<b>`</b>	Anonymise names
	,,	Anonymise localities
		Anonymise species
Analysis	Variable exploration	PCA
	·	Collinearity
		Correlation
	Unimodal tests	Linear Models
		$\chi^2$
		Student
	Statistical models	Generalised Linear Models
		Generalised Additive Models
		Random Forest
	Models Evaluation	Evaluation metrics (e.g. AIC, Jaccard)
		Validation methods
	Projections	Geographical projections
		Temporal projections
Representation	Plot	Raw variables
nepresentation		Modelled results
	Мар	Observations
	r	Projections

398 <u>A f</u>Few changes in code-writing habits can enhance the reusability of the 399 analytical procedure by generating easy-to-understand analytical procedure without investing much time. It is best to develop each elementary step 400 directly in separate code files and to give details of the order in which 401 elementary steps are used for each analytical workflow. To ensure 402 reproducibility and traceability of the results, each computation of the 403 analytical workflow should be associated with the details of the parameters 404 settings and datasets used. From a practical point of view, a couple of 405 recommendations could be made for coding elementary steps in order to 406 facilitate generalisation and ease the reuse. Once each elementary step is 407 defined, we recommend all dependencies (e.g. software version, packages, 408 libraries and their versions) to be set at the same place, at the start of the 409 code, followed by modular parameters (e.g. input file location and name, 410 column selection, modelling parameters, data specificities, output saving 411 412 location). When the script of the elementary step is completed, modular parameters should be the only part of the code that may be modified in 413 future reuse. Dependencies and subsequent computational tasks should be 414

left untouched to ensure the integrity of the analysis and then, reproducibility.
In the end, it is best to add an open-source license to any analytical
procedure shared publicly (*e.g.* MIT, GPL). It permits to clearly state the terms
and conditions of diffusion, share and reuse.

As such, atomisation and generalisation may overcome social or psychological barriers related to transparent sharing, either related to securing ownership (*e.g.* DOI) and to embarrassment or fear during a peerreview process (Gomes *et al.*, 2022).

Atomisation and generalisation are related and complementary concepts. Atomisation into adequate elementary steps is necessary to properly generalise an analytical procedure as it permits to enhance the modularity of the procedure and its capacity to be tailored to different data types. Atomisation and generalisation must be applied from the earliest stages of the programming development of any analytical procedure in order to achieve:

- 430 Greater transparency, even for beginners, since the relevance and 431 coherence of each step and their successive arrangement along the 432 analytical procedure should be appraised independently of the 433 programming skills;
- 434 Time savings;
- 435 Greater reusability;
- 436 Modularity of the elementary steps, to rearrange them differently if 437 needed.
- 438

# 439 Entering a new dimension: the Galaxy-E initiative example

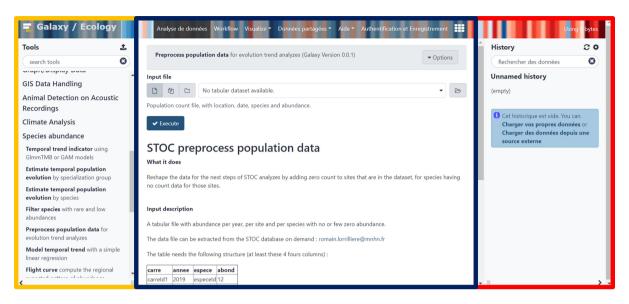
Developing open and properly atomised and generalised analytical 440 procedures can already represent a significant step forward in terms of good 441 442 practicebest practice. Galaxy is a good illustration of atomisation and generalisation with easier management of analytical workflows. The platform 443 proposes many analytical tools that represent generalised and atomised 444 445 elementary steps. These tools are modular and openly licensed, which permits to build generalised workflows as pictured in the Graphical abstract 446 447 ₿.

Galaxy-E is mostly aimed at scientists that process biodiversity data and already have an understanding of the general functionning of the analytical procedures they want to produce. The rationale for a user would be to create or reuse analytical workflows with high FAIRness in a collaborative and open source platform. It can be used for individual analyses as well as for collaborative projects. In some cases, if the analytical procedure is already clearly defined, it can be used by citizens or for teaching.

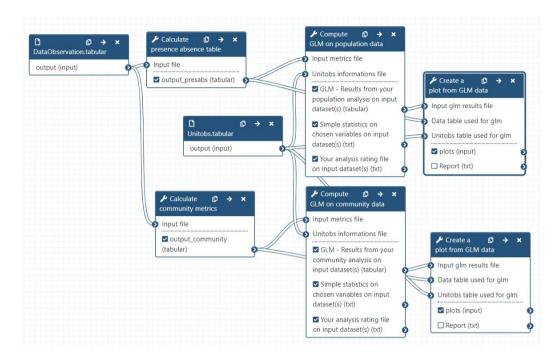
455 It benefits from the same advantages as the framework presented in the
456 previous section and can help achieve a further level of FAIRness as a
457 demonstration platform to package analyses in an accessible and user458 friendly manner (tab. 2).

Galaxy as a demonstration platform to package analyses in an accessible and user-friendly manner can help achieve 459 a further level of FAIRness. Any analytical procedure can be adapted on the platform and Galaxy can be used through 460 the whole data life cycle (https://rdmkit.elixir-europe.org/galaxy assembly). Throughout this note, many ways to 461 contribute to Galaxy are discussed in their conceptual and methodological aspects. One can use off-the-shelf tools, 462 workflows, and tutorials to design an analytical procedure, or suggest, develop, and share new workflows and tutorials, 463 two aspects that do not require coding skills. Eventually, one can modify or develop entirely new tools with any 464 computational language to make them accessible to all users on any Galaxy server. The Galaxy platform emphasises (i) 465 accessibility of tools and data even without programming experience, (ii) reproducibility through the easy creation and 466 reuse of analysis workflows. (iii) transparency through the open-source distribution of underlying codes: and (iv) 467 community support. In 2022, Gomes and collaborators identified 12 barriers to data and code sharing, ranging from-468 unclarity of processes to fear of inappropriate use and insecurities around data and code guality (Gomes et al., 2022). 469 There are different Galaxy servers, at global, continental, and national levels (European and French levels for-470 example), but also according to the fields (e.g., biomedical, ecology, climate). The Galaxy-E initiative is hosted by 471 472 European (https://ecology.usegalaxy.eu) and French (https://ecology.usegalaxy.fr) servers. Datasets can be uploaded on a Galaxy server from a local device, an online server, or a database. Users can then 473 access every available tools (fig. 2, left panel) to modify, explore, and analyse their data. All tools used, parameters, 474 and data (inputs and outputs) of the analysis are saved in a private "Galaxy history" (fig. 2, right panel), documenting 475

476 every step of the analytical procedure and recording the provenance of each output. From any history, the user can
477 extract a workflow (fig. 3) or directly share or publish the history itself.



**Figure 2** - Galaxy-Ecology users' interface https://ecology.usegalaxy.eu. Yellow panel on the left: analysis tool list; blue panel in the middle: current tool interface; red panel on the right: Galaxy analysis history 



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Figure 3 - Representation of a Galaxy workflow in the editing interface of a Galaxy server. Each box represents an analysis tool, and the lines represent the flow of data through the tools

Anyone can use the tools on Galaxy and/or develop new tools and workflows to make them available to all by 484 publishing them in the shared Galaxy ToolShed (https://toolshed.g2.bx.psu.edu/) which ensures that the tools and 485 dependencies can be installed on any Galaxy servers. By definition, a Galaxy workflow already has a degree of 486 atomisation (each tool represents an elementary step) and generalisation and benefits from the same advantages as 487 the framework presented in the previous section in good practices (tab. 2). Any analysis history or workflow can be 488 shared and enriched in parallel by several users, facilitating teamwork, Galaxy-Ecology has implemented workflows for-489 biodiversity data exploration. eDNA processing, general population and community metrics and models. 490 ecoregionalisation. NDVI (Normalised difference vegetation index) computation with Sentinel-2 data among others (see 491 some examples: https://workflowhub.eu/workflows/657) and tutorials for several of them are available on the GTN-492 platform (see https://training.galaxyproject.org/training-material/topics/ecology), 493

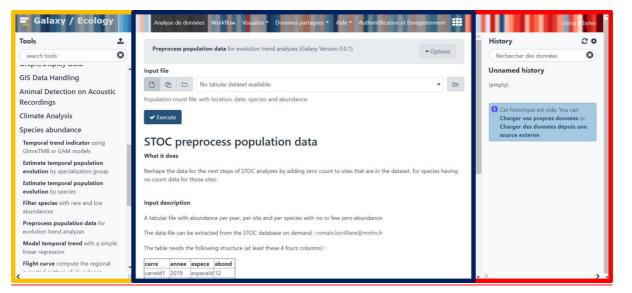
494 <u>Recommendations described in this note regarding the construction of an analytical procedure on Galaxy are meant</u>
 495 <u>to be transposable to local code development or another consistent workflow engine.</u>

# **Table 2** - Comparison between the atomisation-generalisation framework and Galaxy for the achievement of good practicebest practices. Limitations are occasionally raised with short advice to mitigate them when relevant

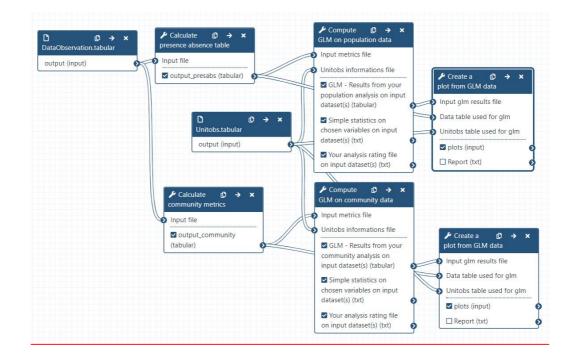
		Atomised-generalised code	Galaxy
Reproducibility and	Environment, software	Can be indicated but possibly hard to manage	Entirely packaged with Conda package manager and BioContainers
transparency	and package versions	Can also be set as an output of the analysis ( <i>e.g.</i> session	Possibility to store analytical procedures as containers for persistent execution
		info)	
		Packages written in each coded elementary step or using a	
	<u> </u>	versioning system such as Conda	
	Inputs and parameters	One must keep track of different parametrisation and input	Automatically tracked and shareable with the "Galaxy history"
		settings at each computation	
	Peer-review	Organisation of the analytical procedure reviewable by non-	Reviewable "Galaxy history" and re-executable workflow
		code developers	<u>Continuous p</u> Peer-reviewed <u>of</u> tools with open-source code
		Code developers might be able to detect errors as it is	Transparency over the development process through Git
		easier in shorter scripts	The workflows can be reviewed by the Intergalactic Workflow Commission (IWC) for best
		Transparency over the development process achievable	practices
		through Git	
	Output provenance	Can be tracked and reproduced in some cases	Tracked with the "Galaxy history" and reproducible with workflow
FAIR principles	Findable	If properly shared	Web-based solution
F - F		F - F - 7	Unified system for data and software citation and attribution
			Tools can be made available on several servers
			Tools can be linked to tools registries and annotated with different ontologies
			Annotated workflows findable on WorkflowHub (https://workflowhub.eu) and Dockstore
			(https://dockstore.org)
	Accessible	If properly shared	Free distribution of tools via the Galaxy ToolShed and workflows via WorkflowHub and
			Dockstore under an open-source licence
	Interoperable	When properly generalised, different elementary steps	Use different software, computational language and library versions on a single platform with
		should be useable in interaction with each other	the Conda package management system
			Workflows exportable in JSON and shareable through several standards (e.g. Common
			Workflow Language; Crusoe et al., 2022 and Research Object Crate; Soiland-Reyes et al., 2022
	Reusable	Generalised elementary steps are reusable and adaptable	Tools, histories and workflows are re-executable, reusable and adaptable with different
		with different analytical procedure, parametrisation and/or	analytical procedure, parametrisation and/or inputs. Open-source code can be used outside c
		inputs	a Galaxy server
Technical and	Understandability	The analytical procedure is clearer when properly atomised	Tools interface, workflow annotations, help sections and tutorials are a valuable help
knowledge gaps	Teaching opportunities	Learning the analytical procedure design separately from	Experimenting with intricate analyses without computer code first
		computing languages, giving structure to trainees	Tutorials and videos from Galaxy Training Network ( <u>https://training.galaxyproject.org</u> )
		Reusability of elementary steps for trainees	Galaxy community
	Computing capacity	Need for a computation cluster if large data or demanding	HPC (High Performance Computing) through an interface
		algorithm	Bulk (meta)data manipulation
Collaboration and attribution	Analysis design and	Achievable through collaborative code-editing applications	With anyone through a Galaxy server
	development		
	Citation	Easy reuse of openly shared elementary steps could lead to	Each tool, workflow, and tutorial are provided with a unique identifier for proper attribution
		higher citation rates	and citation

499 The Galaxy platform emphasises (i) accessibility of tools and data even without programming experience, (ii) reproducibility through the easy 500 creation and reuse of analysis workflows, (iii) transparency through the open-501 source distribution of underlying codes; and (iv) community support. 502 503 Galaxy is ready to use and has proved its efficiency and suitability in other research fields, including genomics and climate science (Knijn et al. 2020; 504 Serrano-Solano et al., 2022). For scientists, from a user's point of view, it 505 506 offers extensive computing power and a graphical interface to use analysis 507 workflows, even without experience in software development. Web-based access allows easy sharing of analytical workflows between collaborators and 508 509 with a broader audience. Galaxy supports tools in almost any computational language, including R and Python, two of the most used languages in ecology, 510 with many packages dedicated to ecological and biodiversity-oriented 511 analyses incorporated (Lai et al., 2019). 512 Anyone can use the tools on Galaxy and/or develop new tools and 513 workflows to make them available to all by publishing them in the shared 514 Galaxy ToolShed (https://toolshed.g2.bx.psu.edu/) which ensures that the 515 tools and dependencies can be installed on any Galaxy servers. Any 516 analytical procedure or workflow can be shared and enriched in parallel by 517 several users, facilitating teamwork. 518 519 Galaxy is a powerful platform enabling researchers to readily move towards best practices. The Galaxy interface mitigates the difficulties 520 associated with library management and code development, which permits 521 simpler access to complex analytical methods. One can focus on the analysis 522 523 itself and its concepts, rather than on syntax difficulties or cluster programming, disconnecting the study of data analysis concepts from the 524 study of computing languages. 525 The platform is community-driven which permits continuous peer review of 526 the platform and of the tools, workflows and tutorials provided. Many tutorials 527 are available on the Galaxy Training Network (GTN) which is a valuable asset 528 to the accessibility and reusability of tools and workflows (Batut et al., 2018; 529 Hiltemann et al., 2023). 530 If enough researchers and experts start using and contributing to the 531 platform, the number and content of available analytical procedures could 532 533 expand at the same pace as latest analytical methodologies are integrated to 534 research processes. If a different platform fits best and is more widely used by ecological and biodiversity scientific communities in the end, the work 535 done on Galaxy will not be lost as tools are easily transposable to other 536 interfaces (e.g. scripts directly usable with R, Python, etc., translation of 537 workflows to other workflow engines). 538 There are different Galaxy servers, at global, continental, and national 539 540 levels (European and French levels for example), but also according to the fields (e.g., biomedical, ecology, climate). The Galaxy-E initiative is hosted by 541 (https://ecology.usegalaxy.eu) 542 European and French (https://ecology.usegalaxy.fr) servers. 543 544 Datasets can be uploaded on a Galaxy server from a local device, an 545 online server, or a database. Users can then access every available tool (fig. 546

2, left panel) to modify, explore, and analyse their data. All tools used, 547 parameters, and data (inputs and outputs) of the analysis are saved in a 548 private "Galaxy history" (fig. 2, right panel), documenting every step of the 549 analytical procedure and recording the provenance of each output. From any 550 history, the user can extract a workflow (fig. 3) or directly share or publish 551 the history itself. Workflows are reusable through WorkflowHub 552 (https://workflowhub.eu) or Dockstore (https://dockstore.org) and exportable 553 in CWL and RO-CRATE standards. 554



**Figure 2** - Galaxy-Ecology users' interface https://ecology.usegalaxy.eu. Yellow panel on the left: analysis tool list; blue panel in the middle: current tool interface; red panel on the right: Galaxy analysis history



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560 561 562 **Figure 3** - Representation of a Galaxy workflow in the editing interface of a Galaxy server. Each box represents an analysis tool, and the lines represent the flow of data through the tools

563 Any analytical procedure can be adapted on the platform and Galaxy can be used through the whole data life cycle (https://rdmkit.elixir-564 europe.org/galaxy assembly). One can use off-the-shelf tools, workflows, and 565 tutorials to design an analytical procedure, or suggest, develop, and share 566 new workflows and tutorials, two aspects that do not require coding skills. 567 Galaxy-Ecology has implemented workflows for biodiversity data 568 exploration, eDNA processing, general population and community metrics 569 and models, ecoregionalisation, NDVI (Normalised difference vegetation 570 index) computation with Sentinel-2 data among others (see some examples: 571 https://workflowhub.eu/workflows/657) and tutorials for several of them are 572 573 available on the GTN platform (see https://training.galaxyproject.org/trainingmaterial/topics/ecology). 574 Eventually, one can modify or develop entirely new tools and workflows 575 with any computational language to make them accessible to all users on any 576 577 Galaxy server. 578 Galaxy is an utterly participative platform and several ways to participate to Galaxy exist depending on one's skills, available time, and needs. Anyone 579 can participate to the Galaxy-Ecology initiative by notably: 580 Sharing datasets, histories and workflows; 581 - Giving feedback on servers, tools, and workflows; 582 - Sharing tools and workflows ideas (eventually with code) through Git 583 584 issues; Asking for tool modifications through issues; 585 - Modifying existing tools or proposing new tools through GitHub or 586 <u>GitLab;</u> 587 - Writing or contributing to a GTN tutorial on a specific functionality or a 588 589 workflow on the Galaxy Training Network platform; 590 <u>Create learning pathways, a set of tutorials curated by community</u> experts to form a coherent set of lessons around a topic, building up 591 <u>knowledge</u> (https://training.galaxyproject.org/training-592 material/learning-pathways); 593 - Propose training events and help users in the utilisation of a workflow 594 and tutorial. 595 596 Analyses are rarely computed only once. Any analysis with a 597 generalisation potential is a suitable candidate to be Galaxy-fied. A 598 methodological framework is presented in online supplementary material 599 (https://github.com/ColineRoyaux/Galaxy\_Templates/blob/main/Methods/Meth 600 601 ods%20-%20How%20to%20Galaxyfy%20your%20analytical%20procedure\_.md) at three levels depending on 602 potential interests, computing language skills, and willingness to invest more 603 or less time in the process: (i) 'user' relying on existing Galaxy tools and 604 workflows to analyse data (lower time investment), (ii) 'developer' relying on 605 existing and validated analytical procedure to develop Galaxy tools and 606 workflows (highest time investment), and (iii) 'trainer' relying on existing 607 Galaxy tools to share workflows and create training material (variable time 608

609 <u>investment). The 12 barriers to data and code-sharing raised by Gomes *et al.*,
610 (2022) can be at least partially addressed by Galaxy (see fig. S1).
</u>

611 Galaxy is a powerful platform enabling researchers to readily move towards 612 good practices. The Galaxy interface mitigates the difficulties associated with 613 library management and code development, which permits simpler access to 614 complex analytical methods. One can focus on the analysis itself and its 615 concepts, rather than on syntax difficulties or cluster programming, 616 disconnecting the study of data analysis concepts from the study of 617 computing languages.

The Galaxy Training Network (GTN) is a valuable asset to the accessibility 618 and reusability of tools and workflows (Batut et al., 2018; Hiltemann et al., 619 2023). The Galaxy Training platform (https://training.galaxyproject.org) is an-620 open, FAIR, collaborative platform compiling a variety of tutorials written by 621 researchers, administrators, developers, and other contributors. These 622 tutorials not only aim to teach how to use Galaxy, and take advantage of 623 advanced features such as Interactive Tools (i.e. interactive applications 624 within Galaxy, e.g. Windows desktop, Rstudio, R Shiny apps), but also how to 625 run and interpret scientific analyses through detailed step-by-step guides. 626

**Discussion and limitations** 

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# Levels of good practice

As highlighted in previous sections, there are many <u>good practicebest</u> practices and recommendations existing for analytical procedures, data management, and computational code development. The levels of application of these <u>good practicebest practices</u> fall within a continuum offering many possibilities. From the lowest to the highest <u>good practicebest</u> <u>practice</u> levels for a published work there can be for example:

- 635 Raw data and analytical procedure are not shared, only processed and
   636 interpreted results along with a brief description of methods.
- 637 Pre-processed data is shared, and methods are described in the word 638 limit given by the publisher (example: tables of metrics and how it was
   639 calculated).
- 640 Raw data and source code are shared on a repository. Software and
   641 package versions are not specified and there is no guaranty to be able
   642 to reproduce the analytical procedure.
- 643 Raw data and atomised generalised source codes are shared on a
   644 repository with specified hardware, software and dependencies
   645 versions. Input parameters are recorded in an attached file.
- Raw data is shared with proper metadata and an actionable version of
   the whole analytical procedure is traceable, ready to use and
   eventually reuse on other data types. Such level can be attained
   notably using Galaxy.
- All results and conclusions are published as an executable paper with
   analyses and workflows implemented and executable directly in the
   shared article (Strijkers *et al.*, 2011).

653 Executable Papers (Strijkers *et al.*, 2011) can require significant time and 654 resource investment as well as good knowledge of programming languages, 655 making it an admirable but hard-to-attain goal.

Atomisation and generalisation of computer codes can represent a 656 relatively low investment strategy to attain certain levels of best practices 657 such as transparency and reusability. It also carries advantages such as 658 easier peer review, modularity of analytical procedures and, consequently, 659 660 time savings. Indeed, applying the framework is not sufficient to attain the highest levels of best practices. For reproducibility and transparency, the 661 management of the environment, softwares and package versions can be 662 663 hard to maintain and record. A comprehensive tracking of input, ouputs and codes requires meticulous management of files arborescence in the 664 environment. Additionnaly, non-code developers will be able to partially 665 review the analytical procedure only if the workflow is clearly outlined in an 666 adapted format (e.g. table, graphical representation). Accessibility and 667 findability of the atomised and generalised analytical procedure is dependent 668 of its proper sharing (e.g. persistent link, open repository). 669

On Galaxy can represent an easier gateway towards higher levels of best 670 practice , as any available tool can be easy to use. Sharing sharing a complete, 671 detailed and (re-)executable analytical procedure is facilitated as through 672 provenance is trackinged and metadata is automatically metadata 673 enrichementd. Finally, a Galaxy history or workflow can be made accessible 674 to anyone (See methods section for details on the use of Galaxy). In 675 comparison, many scientific workflow management systems, such as 676 Snakemake, Nextflow or the R package Targets, operate from the command 677 line. In ecology, numerous initiatives have tried to introduce such systems, 678 starting with more user-friendly solutions. For example, the KNIME and Kepler 679 680 systems with the CoESRA initiative (Collaborative Environment for Scholarly Research and Analysis) in Australia; Taverna with the BioVeL initiative 681 (Biodiversity Virtual e-Laboratory) in Europe; or very recently, the BON in a 682 Box pipeline engine. These systems are more accessible to new users by 683 offering a graphical interface while achieving high specificity (Berthold et al., 684 2007; Hardisty et al., 2016; https://boninabox.geobon.org/). However, good 685 computer programming or scientific workflow management knowledge is still 686 687 necessary to use these applications correctly.

In comparison to the atomisation-generalisation framework, Galaxy can be rightfully seen as heavier for experienced programmers as it requires to learn to use a new platform. Additionally, mMore effort may be required on Galaxy when an additional analytical step needs to be developed, but the Galaxy community can be an efficient crutch on which hard-pressed scientists can rely. Indeed, one can ask for help on the implementation of tools whether one knows computing languages and can share their code or not.

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### 696 A deeply collaborative initiative

697 Galaxy is an utterly participative platform. Any analysis history or workflow
 698 can be shared and enriched in parallel by several users, facilitating teamwork.
 699 As discussed earlier, several ways to participate to Galaxy exist depending on

one's skills, available time, and needs. In the methods section, three ways to-700 participate to Galaxy are distinguished: "as a user", "as a developer" and "as-701 a trainer". One is not confined to only one of these roles; this distinction is 702 more of a handy way to give structure to the methodology depending on 703 one's skills, available time and needs. Anyone can participate to the Galaxy-704 705 Ecology initiative by notably: Sharing datasets, histories and workflows; 706 Giving feedback on servers, tools, and workflows; 707 Sharing tools and workflows ideas (eventually with code) through Git 708 issues: 709 Asking for tool modifications through issues; 710 Modifying existing tools or proposing new tools through GitHub or GitLab; 711 712 Writing or contributing to a GTN tutorial on a specific functionality or a workflow on the Galaxy Training Network platform; 713 Create learning pathways, a set of tutorials curated by community experts 714 to form a coherent set of lessons around a topic, building up knowledge 715 (https://training.galaxyproject.org/training-material/learning-pathways); 716 Propose training events and help users in the utilisation of a workflow and 717 tutorial. 718 Galaxy is community-driven which permits continuous peer review of the 719 platform and of the tools, workflows and tutorials provided. If enough-720 researchers and experts start using and contributing to the platform, the 721 number and content of available analytical procedures could expand at the 722 same pace as latest analytical methodologies are integrated to research 723 processes. If a different platform fits best and is more widely used by 724 ecological and biodiversity scientific communities in the end, the work done 725 on Galaxy will not be lost as tools are easily transposable to other interfaces 726 (e.g. scripts directly usable with R, Python, etc., translation of workflows to 727 other workflow engines), histories shareable as files and workflows reusable 728 729 through WorkflowHub (https://workflowhub.eu) or Dockstore (https://dockstore.org) and exportable in CWL and RO-CRATE standards. 730 Galaxy-Ecology has implemented workflows for biodiversity data 731 732

exploration, eDNA processing, general population and community metricsand models, ecoregionalisation, NDVI (Normalised difference vegetationindex) computation with Sentinel-2 data among others (see some examples: https://workflowhub.eu/workflows/657) and tutorials for several of them areavailable on the GTN platform (see https://training.galaxyproject.org/trainingmaterial/topics/ecology).

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## **Conclusion**

This article <u>note</u> showcases a simple proposition to achieve good practicebest practices in analytical procedures with two plain guidelines: atomisation and generalisation. This straightforward framework represents a different manner to think and build analytical procedures; it doesn't require using a new technology or learning to use a new software. In terms of attaining higher levels of best practice, whether it is through the atomisation-

generalisation framework, Galaxy, a combination of the two or otherwise, the 746 optimal approach is to be determined by individuals depending on their 747 interests, projects, and available resources. Relying on existing solutions as 748 much as possible is, in our perspective, an efficient way to achieve a better 749 understanding of good practicebest practices and their implications. Given 750 751 the current environmental crisis, science has the major political and social 752 responsibility to maintain good levels of transparency, reproducibility and 753 efficiency.

## 754 Methods - How to Galaxy-fy your analytical procedure?

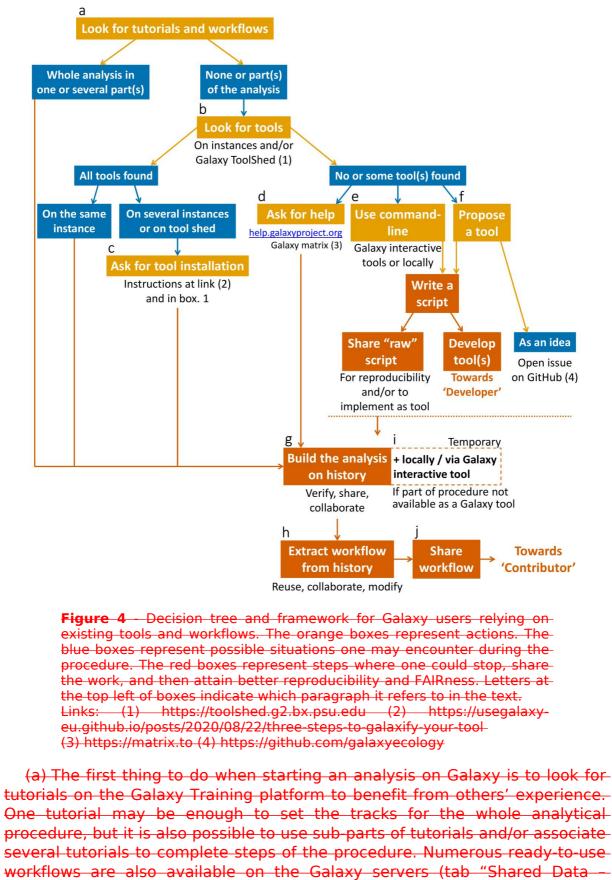
Analyses are rarely computed only once. Any analysis with a 755 generalisation potential is a suitable candidate to be Galaxy-fied. This-756 methodological framework is presented at three levels depending on-757 potential interests, computing language skills, and willingness to invest more 758 or less time in the process: (i) 'user' relying on existing Galaxy tools and 759 workflows to analyse data (lower time investment). (ii) 'developer' relying on-760 existing and validated analytical procedure to develop Galaxy tools and 761 762 workflows (highest time investment), and (iii) 'trainer' relying on existing 763 Galaxy tools to share workflows and create training material (variable timeinvestment). Of course, learning to use a new platform and trying to look 764 differently at analyses is time consuming in the short term, but saves time in-765 the long run. Even if in the end the analysis is not made available on Galaxy, 766 the work is not lost as each step helps the analysis to reach a higher level of 767 good practice. 768

### 769 Guidelines "as a user"

Whether one wants to design a new analysis directly on Galaxy or has-770 already an established analytical procedure and wants to adapt it on Galaxy 771 to make it easier to review and reuse, the following steps are approximately 772 the same. As Galaxy already is a workflow-oriented platform with atomisation 773 of steps, "atoms" of the analysis are apparent while building the analysis on 774 775 Galaxy. The Galaxy platform offers many options that can be explored using the 776 quided tours of the interface (on the welcome page or tab "Help - Interactive 777

Tours"). Several tutorials are also available on the Galaxy Training Network
 (https://training.galaxyproject.org) to learn how to use Galaxy (e.g. topics "Introduction to Galaxy Analyses", "Using Galaxy and Managing your Data").

- 781 Main steps of the implementation of an analytical procedure on Galaxy as a
- 782 user are represented on figure 4.



799 Workflows") or could be imported from WorkflowHub or Dockstore, one may 800 find one or several workflows to complete its analysis. High-quality peer-

801 reviewed Galaxy workflows are reported by the Intergalactic Workflow-Commission (IWC, https://github.com/galaxyproject/iwc). Additionally, it is 802 possible to seek for help by asking on the Matrix channel 803 (https://gitter.im/Galaxy-Training-Network/Lobby) or by opening a topic on 804 the Galaxy Help (https://help.galaxyproject.org). 805

(b) If the whole analytical procedure has not been fully covered with 806 available tutorials and workflows, almost 10,000 tools are available on the 807 Galaxy Tool Shed (https://toolshed.g2.bx.psu.edu) to connect the dots. 808

- (c) One or several helpful tools might not be installed on the used Galaxy 809 server and one may need to ask for an installation (See box. 1 Ask for tool 810
- 811 installation).

- Ask for tool installation. See https://usegalaxy-812 Box 1 eu.github.io/posts/2020/08/22/three-steps-to-galaxify-your-tool/ 813 \_for\_ 814 more details

Fork: Act of creating a copy of a repository in one's personal space-Commit: Act of submitting a modification to a file

Pull Request (PR): Act of proposing one or several Commit(s) to be integrated

Merge: Act of accepting the PR and integrate the modification proposed on the repository

Galaxy tools installation process is accessible to anyone, it is often explained directly in the "Read me" file on the server tools

repository (usually on GitHub or GitLab). To ask for the installation of a tool one must: Look for the tool repository on the Galaxy Tool Shed;

Look for the domain tools repository (e.g. https://github.com/usegalaxy-eu/usegalaxy-eu-tools for all Galaxy Europe servers; https://gitlab.com/ifb-elixirfr/usegalaxy-fr/tools for Galaxy France);

Fork this repository and look for the .yaml file corresponding to the used server (e.g. ecology.yaml for the

https://ecology.usegalaxy.eu and https://ecology.usegalaxy.fr servers);

In the .yaml file, make a Commit to add the following lines with the name and owner of the tool (written on the tool repository on the Galaxy Tool Shed) along with a suggested tool panel section in which the tool can be sorted:-

> name: pampa\_presabs owner: ecology tool\_panel\_section\_label: 'Species abundance' <u> ....</u>

PR the modification on the domain tools repository and wait for server maintainers' approval (merge) and/or suggestions. The installation of tools might be rejected if the peer-review process or relevance of the proposed tool is not adequate in the server maintainers' opinion.

- If there are still gaps in the analytical procedure that none of the existing 815
- tools can fill, several options are available: 816
- (d) Ask for help (see end of bullet a). 817

(e) Temporarily fill the gap with a command-line code locally or through a 818 Galaxy Interactive Tool (e.g. Rstudio, Jupyter notebook and Ubuntu desktop-819 interactive tools). The code can be shared or not. 820

(f) Propose a new tool by sharing the idea through a GitHub issue 821 (https://github.com/galaxyecology; preferably along with a code if existing). 822 Details on the task aimed and awaited input and output (i.e. full-823 specifications) of the tool along with references are of great help for potential 824 developers who may take over tool development. If one wants to try tool 825

- development, see section 'As a developer'. 826
- (g) Through these steps of looking for tutorials, workflows, and tools, the 827 analytical procedure is progressively designed on the Galaxy history. As each 828 Galaxy tool, parametrisation and provenance of each file produced is tracked 829 in the Galaxy history, one can try several tools with different parameters to 830 compare and find out which configuration seems the best. The Galaxy history 831

can be shared to anyone through a link to collaborate on the analysis or in a
 peer-review process.

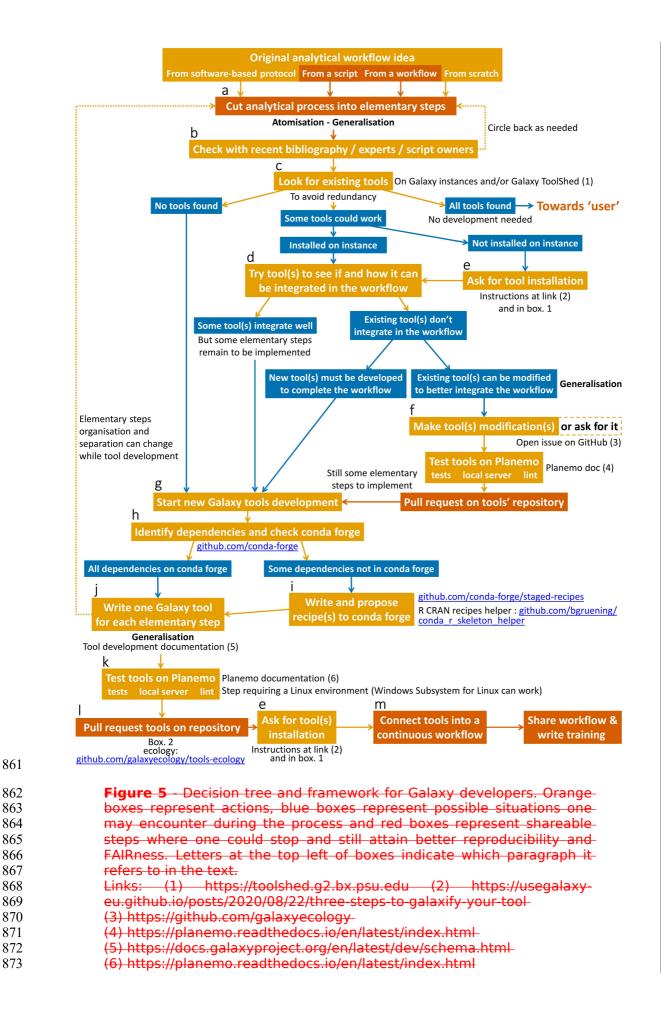
(h) When parametrisation stage is done and the analytical procedure is
 complete, one can extract a workflow to reuse the analytical procedure on
 new datasets.

(i) In the case of a missing tool and part of the analytical procedure is 837 temporarily performed outside Galaxy, one can build separate workflows, 838 between which data is downloaded to make required steps locally. A better 839 temporary solution is to program the launch of Galaxy Interactive Tools (e.g. 840 Posit (R), Jupyter notebooks, and Ubuntu desktop interactive tools) in the 841 workflow to keep most of the procedure on Galaxy. In this case, provenance 842 tracking can be secured partially by saving created objects, command history-843 (e.g. Rhistory), and running environment for example. 844

(j) Extracted workflow(s) can be shared with others for feedback or
collaboration, but it can also be shared publicly on Galaxy server(s) and/or
integrated to an article. When starting to share openly workflow(s), one is a
Galaxy contributor as well as a user (see section "As a trainer").

849 Guidelines "as a developer"

850 Developing Galaxy tools requires time investment, especially at the beginning to understand how Galaxy works and the architecture of the tools. 851 The development procedure can vary depending on the origin of the 852 analytical workflow idea which can be (i) existing code, a package, or a 853 workflow implemented elsewhere, (ii) an idea from a user proposal, (iii) a 854 published article or a personal need, and even (iv) an analytical procedure-855 using originally several interfaced tools. When an analytical procedure was 856 originally designed with atomisation and generalisation of elementary steps-857 in mind, the process of developing Galaxy tools should take a lot less time. 858 Main steps of the implementation of an analytical procedure on Galaxy as a 859 developer are represented on figure 5. 860



874 (a) The atomisation process starts at early stage of the design of an
875 analytical workflow before writing any computer code. Atomisation into
876 elementary steps provides clarity to the development phases. Ultimately, one
877 elementary step equals one Galaxy tool and the modular parameters878 identified in the code for generalisation would be those that appear on the
879 tool interface.

880 (b) One can start by splitting essential steps of the analysis (e.g. preprocessing, analyses, representations) and detailing each elementary step-881 afterward to get different atomisation resolutions (tab. 1; fig. 1). The first 882 atomisation is not a permanent choice and will certainly be refined over the 883 course of the development process. It is mainly useful as a medium for 884 885 researchers and other scientists to give feedback on the projected architecture of the workflow and to have an overview of the analytical 886 procedure. As for any analysis, one must check if potential issues or red flags 887 were raised by the community on the methods used and take it into account 888 in the architecture of the workflow. At this point, any products generated 889 from the atomisation process can be shared and be useful to the scientific 890 community. For example, sharing a written description or a schematic-891 representation of the steps and organisation of an analytical procedure-892 (coded or not) is a valuable help for anyone trying to make a similar analysis. 893

(c) As a user would do and before starting tool development, one mustlook for existing tools on Galaxy servers and Galaxy ToolShed(https://toolshed.g2.bx.psu.edu) to avoid redundancy. If all needed tools are
available, one can directly build their workflow on Galaxy, see 'As a user'
section. Many tools are available on Galaxy for data manipulation. If one
needs a particular format or type of data there is high probability that it can
already be handled on Galaxy.

901 (d) If some tools could work in the workflow, one must test it to see if and
 902 how it can be integrated.

(e) In the case some tools are not installed on the Galaxy server, ask for tool installation (see box.1)

(f) Selected tools might not integrate precisely as aimed, if the input or 905 the output is not formatted as projected in the primary workflow design, 906 other tools added before and/or after might solve the problem. If such tools 907 are not available or the problem is more about a missing parameter or 908 methodology, it might be more coherent to modify existing tool(s) than 909 developing entirely new ones. One can open a new GitHub issue to ask for 910 modifications on the tool repository (found on the Galaxy ToolShed) or 911 directly suggest modifications on the tool. When modifying a tool, the process-912 913 is approximately the same as for developing an entirely new tool (explained in the next paragraph) only the Pull Request for modifications should be 914 915 opened on the tool repository.

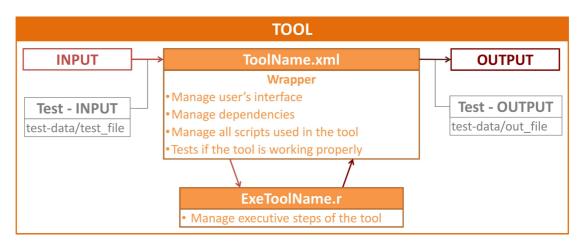
916 (g) The Galaxy community has made available a lot of documentation
917 resources for tool development on the GTN Training platform (category918 "Development in Galaxy"; https://training.galaxyproject.org/training919 material/topics/dev) and on the General Galaxy documentation920 (https://docs.galaxyproject.org;

921 https://docs.galaxyproject.org/en/latest/dev/schema.html).-

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Galaxy tools have a common architecture (fig. 6). Each tool consists of an XML (Extensible Markup Language) wrapper which defines input file(s) and parameters that are presented to the end-user in the Galaxy web interface ("ToolName.xml" in fig. 6). Inputs provided through the interface can be presented in any computing language ("ExeTeelName.r" in fig. 6)

- 926 processed with code in any computing language ("ExeToolName.r" in fig. 6).
   927 Outputs of the code are also specified in the XML file and are made available
- 928 to the user in the Galaxy history at the end of the computation.



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**Figure 6** - Schematic representation of the simplified architecture of an example Galaxy tool using R language. From the input files and parameters provided by the user, the tool will launch an analytical procedure through the XML and R files to produce the outputs.

At least one unit test is mandatory to make sure a tool works and produces the expected outputs. This also facilitates maintenance, as tests will indicate if the functionality is preserved after tool updates. To do so, the test is written in the XML file with all parameter settings, input and expected output files (stored in a sub-directory "test-data") or characteristics of the expected output.

940 This organisation can be more elaborate, especially when developing 941 several tools at the same time. For example, parts of XML files may repeat 942 themselves in the different tools and one can create a supplementary XML 943 file to write this repeating part once as a macro and call ('expand') it as 944 needed, which saves time and space. The same type of repeating patterns 945 can occur in the computing code and one should create a functions file to 946 avoid copy-pasting of many lines in several separate code files.

947 Detailed documentation of the XML wrapper files is available in Galaxy, 948 see https://docs.galaxyproject.org/en/master/dev/schema.html, as well as 949 tutorials (https://gxy.io/GTN:T00117). An empty Galaxy tool template in R 950 language is available in the following repository: 951 https://github.com/ColineRoyaux/Galaxy\_Templates/tree/main/R\_Tool\_templa 952 te.

(h) To begin development, it is best to have knowledge of the required
 informatics dependencies of the tool(s) such as software versions, packages
 and their versions to directly check their availability on Conda Forge
 (https://conda-forge.org/feedstock-outputs).

(i) Some dependencies might not be available, and, in this case, one mustwrite and propose a recipe to the Conda Forge on GitHub-(https://github.com/conda-forge), for guidelines see https://condaforge.org/#add\_recipe. For Python and R packages available on Pypi or CRANrespectively, helper codes are available to automatically generate recipes, see https://github.com/conda/grayskull and https://github.com/bgruening/conda\_r\_skeleton\_helper (by B. Grüning), respectively. Dependencies of the Galaxy tools are called in the XML file.

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(i) Generalisation of computational code is especially important while 965 developing the Galaxy tool to make sure the tool is useful to the largest 966 audience. It is difficult to think about all possible purposes of a tool, one will 967 968 likely miss some aspects but as Galaxy is a participative platform, anyone 969 can ask for modifications or make it themselves. The format of the input fileis a critical aspect of developing a Galaxy tool, while other aspects of the 970 format can be left to the users' choice or imposed. For example, on Galaxy, 971 the preferred format for table input is tab-separated values (TSV or "tabular"). 972 973 Many tools on Galaxy are available to convert file formats (e.g. from CSV totabular). 974

975 For example, a typical choice to make as a developer when developing a tool dealing with tables is to ask the user to specify through the interface 976 which column contains a specific variable, or to require a column name to be 977 present in the input file for the tool to find the variable. The first option is 978 979 more generalised as it is easier for the user to select a column directly on the interface rather than change column names in the data files. The second 980 option can however be chosen when the tool uses a lot of columns in 981 different input tables or has a lot of intricate parameters to avoid 982 unnecessary complexity of the tool interface. This option can also be 983 consistent for tools using input data file written in a standardised way, as 984 Darwin-core data standard for example. 985

986 Depending on the type of manipulations and analyses made in the tool, many parameters might be useful for users to customise such as the type of 987 model, the distribution law of the data, the corrections to make on the data, 988 989 the level of resolution or the type and format of output(s). Prior discussions on the workflow with experts and researchers on the analytical procedure can-990 permit to raise important parameters for the users to set. Another good way 991 992 to get a view on what kind of parameters can be useful for users is to check directly for parameters in the functions used in the computational code and 993 identify which ones are important for the computation and might be critical 994 for users to set. These parameters can be provided with default values if the 995 996 user does not provide a custom value. An "advanced parameters" collapsiblesection can also be implemented to keep the interface simple while still 997 permitting flexibility for experimented users. Finally, to check if a workflow is 998 999 properly generalised, one can seek input files of different origins from open data repositories or ask scientists to test their tools. 1000

1001 It is impossible to prevent all possible misuses of software and such events
 1002 occur also when using command-line functions. Implementation of error and
 1003 warning messages in the computing code is the best way to avoid misuse
 1004 (*e.g.* wrong input format or parameter selection). One can also use the

interface, the help section of tools, and training to help users to set 1005 parameters properly and raise red flags on the use of tools and workflows 1006 (e.g. the tool cannot be used on some types of data, types of modelling 1007 interact badly with some parameters settings or data distributions). If 1008 possible, implementing verification steps in the tools to give feedback to the 1009 1010 user on how the computation went is also a good way for the user to get 1011 hindsight on the results (e.g. quantity of data that couldn't be used in the tool, models' evaluation variables, summary plots). 1012

(k) To verify tools syntax (lint), run unitary tests (test), and deploy a local 1013 Galaxy server to test tools interface (serve), one must use Planemo, the 1014 Galaxy Software Development Kit (Bray et al., 2023). Planemo is a command-1015 line tool used on a Linux environment (see documentation-1016 https://planemo.readthedocs.io/en/latest. For Windows users, Planemo can-1017 work on a WSL (Windows Subsystem for Linux) or using cloud development 1018 environment like GitPod. Galaxy Tool development can take many forms; the 1019 computational code can be developed beforehand on the local environment 1020 or, together with the XML file and be tested directly through a local interface 1021 deployed for testing. Each strategy has different pros and cons depending on 1022 the type of analytical procedure, the origin of the workflow, and the 1023 developer personal preference and knowledge. 1024 (I) When ready, tool(s) can be proposed to a collaborative Galaxy tool 1025

repository (for ecology: https://github.com/galaxyecology/tools-ecology; see 1026 1027 box. 2 for procedure on GitHub) for peer-review by the community.

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**Box 2** - Definitions of Git terminology and procedure for proposing a tool to a Galaxy repository

Merge: Act of accepting the PR and integrate the modification proposed on the repository

One has to fork the repository to add their new tool with a Commit and propose a PR against the original Galaxy repository with a brief description of the aims of developed tool(s) (PR example: https://github.com/galaxyecology/tools ecology/pull/50). When a PR isopened on the repository, verification ("Check jobs") of the tool(s) compatibility, syntax, development good practices and properrunning are made automatically. If there are problems, one can check output logs of what went badly and try to correct it whilescientists invested in the Galaxy community give feedback on the tool(s). When checks are finally passed and code is peer reviewed by the community, the PR is merged and the tool(s) made available on the Galaxy ToolShed within a few days. One may then ask for toolinstallation on any server (see box. 1 Ask for tool installation).

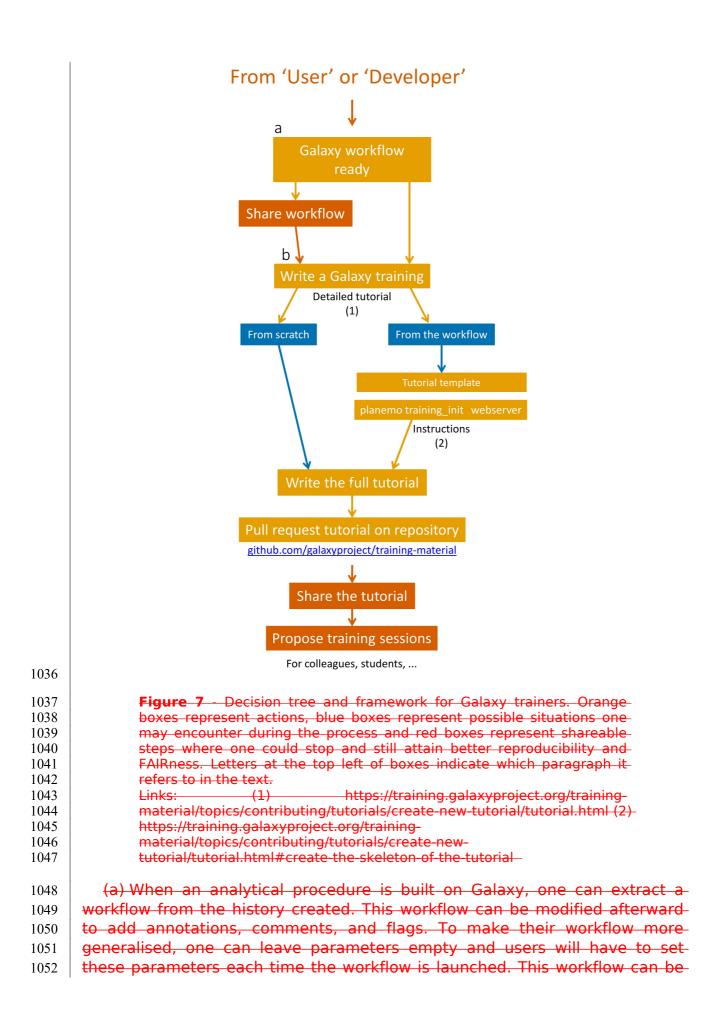
(m) Once all developed tools are available on the Galaxy server, one can 1030 build a workflow as a user would do, share it and eventually write a training 1031 on the use of the workflow, see section "as a trainer". 1032

- 1033 Guidelines "as a trainer"
- Main steps of the implementation of an analytical procedure on Galaxy as-1034 a trainer are represented on figure 7. 1035

Fork: Act of creating a copy of a repository in one's personal space-

Commit: Act of submitting a modification to a file

Pull Request (PR): Act of proposing one or several Commit(s) to be integrated



1053 shared to contribute to Galaxy. Ultimately, it could be submitted to IWC and
 1054 be made available on WorkflowHub and/or Dockstore.

(b) Eventually, one can write a tutorial on the GTN or a blog post on the 1055 Galaxy Community Hub to get better visibility and broadcast valuable 1056 elements on the use of the workflow. GTN tutorials are written in markdown. 1057 1058 One can start from scratch, but it is easier to start from a template generated from an existing Galaxy workflow using the dedicated webserver 1059 (https://ptdk.apps.galaxyproject.eu) or the command-line software Planemo-1060 (documentation: https://planemo.readthedocs.io/en/latest). Indeed, this-1061 approach only requires adding any needed explanations between the auto-1062 generate "hands-on" boxes containing tools and parameters instructions. 1063 1064 Many tutorials explain the different ways to contribute to the GTN (e.g. 1065 tutorials, slides, videos, training sessions, guizzes) in the contributing topicon the GTN: https://training.galaxyproject.org/training-1066 material/topics/contributing Introduction on the creation of a new hands-on-1067 tutorial is detailed in this tutorial: https://training.galaxyproject.org/training-1068 1069 material/topics/contributing/tutorials/create-new-tutorial/tutorial.html. Like tools, contributions to Galaxy Training Material are proposed through GitHub 1070 1071 (https://github.com/galaxyproject/training-material). Available tutorials are 1072 publicly and freely available and can be openly shared to colleagues and students and be used during courses and training sessions. 1073

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**Appendices** 

**Table S1** - Barriers and solutions to data and code-sharing raised by Gomes *et al.* (2022), along with corresponding solutions on the Galaxy-platform.

<b>Barriers</b>	Solutions and arguments from Gomes et al. (2022)	How Galaxy addresses the barrier
Unclear-	Use FAIR principles	FAIR and workflow-oriented platform
sharing-	Try, even if it is not perfect	Easy sharing of computational procedures ("Galaxy history"
<del>process</del>	Look for online resources	and/or workflow) as a link or a file attached to a publication
•	Ask editorial support staff and institutional libraries	Available online resources and forums for help
Complex-	Process and clean data with reproducible code	Reproducible workflows and visualisation of analytical
workflows	Detailed description of data processing steps-	procedure with the interface (fig. 3)
	Use non-proprietary files or softwares	"Galaxy history" tracks provenance of outputs and details of the
	Avoid manual tasks	data processing steps
		Possibility to add annotations and write a tutorial
		Open source platform
		Manual tasks can be recorded in workflows
Large data-	Free cloud storage	Free cloud storage (storage extension on demand) and High
files	Bundle smaller datasets	Performance Computing
Insecurity	Share to trusted peers and/or on pre-prints servers	"Galaxy history" and workflow record the whole analytical-
	before formal peer-review	procedure, it is private by default and can be shared to specific-
	Review before publication ensues in higher-quality	users or through a link making review by trusted peers easier
	results	and faster before public sharing
	Foster an inclusive environment promoting growth	Peer-reviewed tools
	over criticism and shame	
	<u>"Perfect code" doesn't exist</u>	
Unclear value	Uncertainty about potential reuse should not-	Sharing an analytical procedure is not only relevant for others'
	present a barrier to sharing	reuse but also for collaboration, peer review, and teaching-
		Sharing tools or workflows with Galaxy enables overcoming this
		uncertainty
		Methods of the note aims to facilitate this process and ensure it
		is properly made, adding a layer of clarity regarding the value of
		shared codes
Inappropriate-	Metadata information with thorough description of	Raise major red flags or potential misuse in the help section
use	datasets and processes, terms and consideration of	and/or in the tool execution by validating input before tool-

	Dista	reuse and any limitations, assumptions, caveats, and shortcomings Include contact information-	execution. Implemented errors and warnings in the code to prevent- directly prohibitive use of tools. Write execution suggestions and guidelines in the workflow- annotations and/or associated tutorial. Possibility to produce editable report when executing a- workflow or from the "Galaxy history"			
	Rights	Use open repositories instead of attaching code and- data directly to the article as supplementary- material Use data and code licenses Seek for help with institutional libraries and offices- dedicated to copyright, open science and- commercialisation	Open-source platform and tools shared through public servers- prevents copyright issues Each Galaxy tool related code must have a license. Annotation of- workflows with license Use of GitHub (or GitLab) to share code and workflows			
	Sensitive- content	Aggregating, generalising or anonymising data	Sharing data and analytical procedure is up to the user Available tool to anonymise geographical coordinates on Galaxy			
	Transient- storage	Archive data in permanent repositories Avoid proprietary files (e.g. Microsoft suite files) Use tools to promote backwards compatibility and portability of softwares and packages within- different operating systems (e.g. containers, Jupyter- notebooks)	Use of Software Heritage through GitHub to archive code Promotes non-proprietary files (e. g. TSV, fasta) Version-controlled tools to ensure the consistency and- persistence of analyses even over updates Conda package manager and BioContainers to ensure cross- operating system compatibility for any programming language Containerisation to ensure cross infrastructure compatibility (Grüning <i>et al.</i> , 2018) Possibility to execute and share Jupyter notebooks Development repositories available in the Galaxy ToolShed			
	Scooping	Data and code sharing increases opportunities for- collaborations Use pre-print servers to make first claim to a- research project "Those who collect data and develop code remain- best positioned to undertake future analyses" (pp. 6)	Credit of tools are displayed on the interface Users creating a "Galaxy history" can export a reference list of each tool used, facilitating credit attribution. Data can be shared privately through a link while being prepared- for publication, or while under embargo.			
	Lack of time	"Despite the upfront time required, sharing research- data and code can ultimately save time for individual- researchers and their collaborators, as well as for- others who want to reuse it" (pp.7) Begin the research project taking account of future- sharing of data and code	More time-consuming in the short term as learning to use a new- tool is time-costly but time is saved in the long run as analyses- can be re-executed with different parameters, data, or by- different users It can help reduce peer review time with possible reproduction- of results and easy access to analysis details through the- workflow-interface			
	<del>Lack of</del> incentives	"Sharing data and code can increase visibility and- recognition of a researcher within the scientific- community []. It can also help develop open- science habits that increase efficiency, and- contribute to a better understanding of one's own- data and code" (pp.7)	Facilitates sharing and reuse of analytical methods, broader- citations of the article associated with the analysis or- collaborations could naturally emerge			
1078		Acknowled	gements			
1079 1080		ors want to thank Sandrine Pavo and reviews on both the conten	pine for its highly relevant and helpful t and the form of the article.			
1081	Authors	contribution statement				
1082 1083 1084 1085 1086	<ul> <li>C. R. drafted the article text, tables, and figures.</li> <li>C. R. conceptualised the atomisation – generalisation framework with JB</li> <li>M. and Y. L.B. while working on the development of Galaxy workflows.</li> <li>JB. M. and Y. L.B. reviewed and helped rewrite many parts of the draft.</li> <li>Y. R. and D. P. helped inspire and were invested in the early design of the</li> </ul>					
1087 1088 1089 1090 1091	O. N.,	-	ne appliance of the framework. H. R. and S. H. highly enhanced the and content at several stages of the			

1092 H. R, S. H., B. B., A. F., and B. G. are involved in the Galaxy-E initiative and 1093 provided many advices on the redaction of the article and/or on the 1094 development of the initiative.

1095 M. E. and G. M. are involved in Antarctic-oriented Galaxy tool and workflow 1096 development coordination.

1097 C. B., R. L., A. M., Y. B., A. A., T. V. and V. C. developped scripts, tools 1098 and/or Galaxy workflows to contribute to the Galaxy-E initiative.

1099 E. A. developped R scripts and apps used to integrate R Shiny apps as 1100 Galaxy interactive tools and initiate "Research Data management Galaxy 1101 tools".

1102 E. M. and C. U. developed the first training materials for Galaxy-E.

1103 E. T. worked on the use of the first Galaxy-E analysis.

1104 M. D., G. L. and R. J. were coordinating the prefiguration of Galaxy-E 1105 through the 65 Millions d'Observateurs project.

Additionnally, all authors reviewed and approved the article draft.

### 1107

# Funding

Funding were provided by the European Union through the Erasmus+ 1108 1109 project; the Agence Nationale de la Recherche through the 65 Million d'Observateurs and the IA-Biodiv projects; the French National Fund for Open 1110 Science through the OpenMetaPaper project; the European commission 1111 through the H2020, the EOSC-Pillar, and the H2020 GAPARS projects; the GO 1112 FAIR initiative through the BiodiFAIRse Implementation Network; the Blue 1113 Nature Alliance; and the Antarctic and Southern Ocean Coalition. Finally, 1114 1115 funding by the French Ministry of Higher Education and Research were provided for the "Pôle national de données de biodiversité" e-infrastructure. 1116

1117 Conflict of interest disclosure

1118 The authors declare that they comply with the PCI rule of having no 1119 financial conflicts of interest in relation to the content of the article.

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