




1 Self-Guided Decision Support Groundwater Modelling 2 with Python

3 **Rui T. Hugman** ¹, **Jeremy T. White** ¹, **Mike Fienen** ², **Brioch
4 Hemmings** ³, and **Katie Markovitch** ¹

5 ¹ INTERA Geosciences, Perth, Western Australia, Australia ² U.S. Geological Survey, Upper Midwest Water
6 Science Center, Madison, WI USA ³ Wairakei Research Centre, GNS Science, Taupō, New Zealand

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Software

- [Review](#) 
- [Repository](#) 
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7 Summary

8 The [GMDSI tutorial notebooks repository](#) provides learners with a comprehensive set
9 of tutorials for self-guided training on decision-support groundwater modelling using
10 Python-based tools. Although targeted at groundwater modelling, they are based around
11 model-agnostic tools and readily transferable to other environmental modelling workflows.
12 The tutorials are divided into three parts. The first covers fundamental theoretical
13 concepts. These are intended as background reading for reference on an as-needed basis.
14 Tutorials in the second part introduce learners to some of the core concepts parameter
15 estimation in a groundwater modelling context, as well as providing a gentle introduction
16 to the PEST, PEST++ and pyEMU software. Lastly, the third part demonstrates how to
17 implement highly-parameterized applied decision-support modelling workflows. Their
18 aim is to provide examples of both “how to use” the software as well as “how to think”
19 about using the software. A key advantage to using notebooks in this context is that
20 the workflows described run the same code as practitioners would run on a large-scale
21 real-world application. Using a small synthetic model facilitates rapid progression through
22 the workflow.

23 Statement of Need

24 Effective environmental management necessitates transparent acknowledgment of uncer-
25 tainties in critical decision-making predictions, coupled with efforts to mitigate these
26 uncertainties, especially when significant risks accompany management outcomes. The
27 significance of uncertainty quantification (UQ) and parameter estimation (PE) in environ-
28 mental modeling for decision support is widely acknowledged. UQ provides estimates of
29 outcome uncertainty, while PE reduces this uncertainty through assimilating data.

30 Implementing highly-parameterized UQ and PE in real-world modeling can be challenging
31 due to both theoretical complexity and practical logistics. Limited project time and
32 funding also often hinder their application. Open-source software such as PEST ([Doherty,
33 2015](#)) and PEST++ ([Jeremy T. White, Hunt, et al., 2020](#)) provide tools for undertaking UQ
34 and PE analyses. However, the steep learning curve associated with their use and the lack
35 of user-friendly training materials have been a barrier to uptake.

36 There is a growing demand within the environmental modelling community for transparent,
37 reproducible, and accountable modeling processes, driven by the need for increased
38 credibility and rigor in computational science and environmental simulation ([Fienen
39 & Bakker, 2016](#); [J. White et al., n.d.](#)). While some script-based tools enhance the
40 reproducibility of forward model construction ([Bakker et al., 2016](#)), they often overlook

41 UQ and PE analyses. In decision-support scenarios, these analyses are equally vital for
42 robust model deployment as the forward model itself.

43 The uptake of Python for environmental modeling has increased in recent years, due to
44 its open-source nature, user-friendly syntax, and extensive scientific libraries. Python-
45 based tools have been developed to facilitate UQ and PE analyses, such as pyEMU (Jeremy
46 T. White et al., 2016; Jeremy T. White et al., 2021). pyEMU is a Python package that
47 provides a framework for implementing UQ and PE analyses with PEST and PEST++.
48 It offers a range of capabilities, including parameter estimation, uncertainty analysis, and
49 management optimization. Although initially designed for groundwater modeling, pyEMU's
50 methodologies are versatile and can be applied to diverse numerical environmental models,
51 as long as they can be manipulated using text files and generate outputs that can be
52 automatically extracted without manual interference.

53 The tutorial notebooks discussed herein provide a comprehensive, self-guided, and open-
54 source resource for learning decision-support modeling workflows with Python. They
55 are designed to be accessible to a broad audience, including students, researchers, and
56 practitioners who aim to undertake applied environmental decision-support modelling.

57 Story of the Project

58 The Groundwater Modelling Decision Support Initiative (GMDSI) is an industry-backed
59 and industry-aligned initiative. Established in mid-2019, its primary goal is to enhance
60 the role of groundwater modeling in groundwater management, regulatory processes,
61 and decision-making. At the core of GMDSI's mission lies the numerical simulation of
62 groundwater movement and processes. Often, data related to groundwater are limited,
63 leading to uncertainties in simulator predictions. However, despite this uncertainty,
64 decisions must be made, and associated risks must be assessed. Modelling plays a central
65 role in the evaluation of these risks.

66 GMDSI is dedicated to promoting, facilitating, and providing support for the improved
67 utilization of modeling in decision support processes. Its activities endeavor to elevate the
68 role of groundwater modeling in decision-making processes, recognizing the importance
69 of model partner software for UQ and PE, and offering a range of activities aimed at
70 industry engagement, education, practical examples, research, and software development.

71 A majority of groundwater modelers typically rely on Graphical User Interfaces (GUIs)
72 for their modeling needs. However, each GUI has its unique characteristics and varying
73 degrees of compatibility with external software like PEST and PEST++. Creating educational
74 materials for these GUIs would necessitate tailoring content to each GUI's specific features,
75 obtaining cooperation from the GUI developers themselves and potentially lagging behind
76 the latest developments.

77 Decision-support modeling often demands capabilities that surpass what current GUIs
78 can offer. For example, many of GMDSI's worked examples rely on custom-designed
79 utilities or the integration of different software components. Currently, a significant
80 portion of users may not have the expertise to independently implement such advanced
81 approaches. Furthermore, the manual preparation of input files for implementing these
82 complex workflows can be time-consuming. Programmatic workflows, such as those
83 facilitated by pyEMU, offer advantages by reducing the time and user input required for
84 setup and execution. This approach is somewhat analogous to the role played by a GUI
85 but offers added flexibility, allowing users to customize and design their own functions
86 and utilities as needed. However, it comes with the drawback of increased potential for
87 user-introduced errors.

88 Over time, more modelers are turning to Python packages like FloPy and pyEMU for model
89 and PEST++ setup. Unfortunately, the adoption of this approach is hindered by a steep

90 learning curve primarily due to the scarcity of user-friendly training materials. The [GMDSI](#)
91 [tutorial notebooks](#) aim to address this gap by providing a comprehensive, self-guided, and
92 open-source resource for learning decision-support modeling workflows with Python.

93 The roots of the materials making up the tutorial notebooks were from a traditional, week-
94 long classroom course curriculum developed for internal training at the USGS by a subset
95 of the authors of this paper. For this course, the instructors leveraged the power of jupyter
96 notebooks as a mechanism to teach both the fundamental background and application of
97 inverse theory. High-level mathematical libraries in python (and other high-level languages
98 with easy plotting utilities such as MATLAB and R) provide an opportunity for students
99 to explore linear algebra and statistical modeling principles that underlie the PE and
100 UQ techniques implemented in PEST and PEST++. Furthermore, the combination of text,
101 code, and graphics provide an interactive platform for mixing theory and applications
102 and, potentially, providing a template for application on real-world applications. The
103 native support for python makes the connection between worked examples and notebooks
104 seamless and has connections with other worked examples [Jeremy T. White, Foster,
105 et al. (2020); J. T. White et al. (2020); Fienen et al. (2022); [https://github.com/doi-](https://github.com/doi-usgs/neversink_workflow)
106 [usgs/neversink_workflow](https://github.com/doi-usgs/neversink_workflow)]

107 After three iterations of teaching the in-person class, the instructors concluded that the
108 materials and approach were valuable, but came to question the level of retention by
109 students in a 40-hour intensive setting. It is well-documented that without repetition
110 and rapid adoption of new techniques, they can fade quickly from memory ([Glaveski,](#)
111 [2019](#)). As a result, the authors, with support from the GMDSI, endeavored to build on the
112 positive aspects of using jupyter notebooks and explore alternative teaching environments
113 instead of week-long classes. The first major change was to add sufficient narration and
114 explanation to the notebooks to improve possibilities for self-study. The initial design
115 through in-person instruction was to have the notebooks serve as illustrations to assist
116 in a narrative discussion, so bolstering of the explanatory text was necessary to help
117 them stand alone. The next change was to refactor the organization from a strictly linear
118 progression to the current three-part organization discussed below. This led to a hybrid
119 model of self-study punctuated by discussion and background lectures online.

120 Resources

121 A webinar hosted by GMDSI introducing the tutorial notebooks can be viewed [here](#).
122 During the webinar the authors provided an overview of the notebooks, as well as a
123 demonstration of how to use them and introduced an [online self-guided course](#).

124 The [GMDSI](#) web-page also hosts an extensive range of resources and educational material
125 on decision support modelling. These include numerous instructional video lectures,
126 webinar recordings, non-programmatic workflow tutorials, as well as worked example
127 reports describing real-world applications.

128 Software from the PEST suite can be downloaded from John Doherty's web page [here](#). The
129 [user manual](#) contains much useful information. The [PEST Book](#) is also a great resource
130 for learning about the theory underpinning use of the software.

131 Software from the PEST++ suite can be accessed from GitHub [repository](#). The [user manual](#)
132 contains much useful information, as well as theoretical background to the software.
133 Further theoretical background is available in ([Jeremy T. White, Hunt, et al., 2020](#)).

134 pyEMU can be accessed from the Git-Hub [repository](#). The repository contains several
135 example jupyter notebooks. The tutorial notebooks discussed herein provide a more
136 exhaustive and structured learning experience.

137 **Contents and Instructional Design**

138 The tutorial notebooks are structured into three main parts:

139 **Part 0: Introductory Background**

140 Part 0 serves as the foundation, providing essential background material. Learners are
141 encouraged to reference notebooks in Part 0 to polish their understanding of concepts
142 they encounter in Parts 1 and 2. Part 0 is not intended to be a comprehensive resource for
143 all background material, but rather to establish a solid understanding of the basics. The
144 explanations of mathematical concepts are intended to be accessible through visualization
145 and descriptions related to everyday concepts and modelling concepts.

146 Each notebook in Part 0 is standalone and covers a unique topic. These include: -
147 Introduction to a synthetic model known as the “Freyberg” model. This model is used
148 as a consistent example throughout the tutorial exercises, allowing learners to apply
149 concepts in a practical context. - An introduction to the `pyemu` Python package that is
150 used to complement and interface with PEST/PEST++. - Explanation of fundamental
151 mathematical concepts that are relevant and will be encountered throughout the tutorial
152 notebooks.

153 **Part 1: Introduction to PEST and the Gauss-Levenberg Marquardt Approach**

154 Part 1 focuses on the Gauss-Levenberg Marquardt (GLM) approach to parameter estima-
155 tion and associated uncertainty analysis in a groundwater modelling context. This was the
156 foundation of the PEST software for multiple decades and the theory continues to resonate
157 through newer techniques.

158 Part 1 is designed to be accessible without strict sequential dependencies. Learners have
159 the flexibility to explore its contents in any order that suits their preferences or needs.
160 These include: - Introduction to concepts such as non-uniqueness, identifiability, and
161 equifinality. - Introduction to the PEST control file and the PEST/PEST++ interface.
162 - Exploring the challenges of parameterization schemes on predictive ability, as well as
163 how to mitigate them. - Introducing first-order second-moment (FOSM) and prior Monte
164 Carlo uncertainty analysis approaches.

165 While Part 1 notebooks can be largely run in any order, the curriculum was initially designed
166 to start with simple parameterization of a model and to build complexity intentionally
167 throughout the progression of the sequence. The ramifications of simplification and the
168 value of adding complexity are evaluated in the context of the performance of the model
169 in forecasts made outside the parameter estimation conditions. This progression motivates
170 the value of a highly-parameterized approach which is the starting point for many new
171 projects, as explored in Part 2.

172 **Part 2: Python-based Decision-Support Modelling Workflows**

173 Part 2 expands on the foundational knowledge gained in Part 1 and delves into advanced
174 topics related to ensemble-based parameter estimation, uncertainty analysis and optimiza-
175 tion methods. These advanced topics include management optimization and sequential
176 data assimilation. This approach and these advanced topics assume a highly-parameterized
177 approach, as motivated in Part 1. Topics are laid out in manner that reflects real-world
178 workflows, with a focus on practical application of concepts and problem solving.

179 Part 2 is structured with a specific order for learners to follow to ensure a logical progression
180 of topics, inline with a real-world applied workflow. Learners have the option to explore
181 various sequences covering advanced topics, such as: - Prior Monte Carlo analysis -
182 Highly-parameterized Gauss-Levenberg Marquardt history matching and associated Data

183 Worth analysis using First Order, Second Moment (FOSM) technique, - Ensemble-
184 based history matching and uncertainty analysis with the iterative ensemble smoother
185 approach as implemented in PEST++IES, - Sequential data assimilation with PEST++DA, and
186 - Single-objective and multi-objective optimization under uncertainty with PEST++OPT and
187 PEST++MOU.

188 Each of these sequences comprises multiple notebooks to be executed in a specified order.
189 They demonstrate how to execute the workflow, interpret results, and apply the concepts
190 to real-world problems.

191 In summary, the tutorial notebooks are organized to guide learners through a structured
192 learning experience in the field of decision-support groundwater modelling. Part 0 provides
193 foundational knowledge, while Parts 1 and 2 offer progressively advanced content. The
194 authors attest that it is ideal to work through Parts 1 and 2 in their entirety, referring back
195 to Part 0 for additional background. However, this amount of content requires a significant
196 time commitment so, practically, many users will start with Part 2 and, hopefully, be able
197 to apply the concepts to a problem of their own as they progress. Over time, referring
198 back through Part 1 will provide a deeper understanding of some concepts and techniques
199 taken for granted in the highly-parameterized, largely ensemble-based approaches of Part
200 2.

201 Experience of use in teaching and learning situations

202 The notebooks were employed during the [Applied Decision Support Groundwater Modeling](#)
203 [With Python: A Guided Self-Study Course](#) hosted by GMDSI. This self-guided course
204 comprised 5 online sessions, each lasting 1 to 2 hours and focused on the workflows of Part
205 2. During each session the instructors go through a section of the tutorials and expand on
206 some of the concepts. Learners were tasked with going through the notebooks in between
207 sessions to stimulate discussion and questions. Sessions were recorded and can be accessed
208 [on the GMDSI website](#). Beyond the live online sessions, learners were incentivized to make
209 use of the GitHub [Discussions](#) feature to retain a search-engine findable record of common
210 questions.

211 Feedback from the 65 students who participated in the course was anecdotal but informative.
212 Figure (([fig-responses?](#))) summarizes the responses by 34 respondents to four questions,
213 comprising 52%. The majority of respondents indicated a preference for this hybrid
214 self-guided/online instruction approach over an in-person week-long intensive class with
215 only one respondent indicating preference for self-guided study of the course materials only.
216 Just under 60% of the respondents reported being able to keep up with most or all of the
217 assigned self-study notebooks, while 41% reported falling behind. Given 5 categories of
218 comfort level working with PEST++ (1 being most comfortable, and 5 being least) before
219 and after the class, there was a notable shift toward higher comfort level. Interestingly,
220 when evaluating individual responses, the majority (56%) reported being more comfortable
221 with PEST++ after the course (defined as an increase of one level) and 15% reported
222 being much more comfortable (an increase of two levels). However, 21% reported the same
223 comfort level before and after while 24% reported being less or much less comfortable (a
224 decrease or one or two levels, respectively). Without further questions, we cannot know
225 whether these decreases reflect a humble realization that their mastery was less complete
226 than they thought, *a priori*, or whether the material was confounding.

227 Open-ended feedback from the participants was generally positive and also included some
228 constructive criticism. Participants appreciated the opportunity to ask questions and
229 several reported hearing the discussion around other peoples' questions as being valuable
230 and clarifying aspects of the material. The main critical suggestions included incorporating
231 more real-world examples rather than relying, as we 100% did in the notebook design,
232 on the synthetic model. Participants also noted the twin challenges of a large amount of

233 information coupled with trying to be accountable to keep up in the class as potentially
 234 limiting the value relative to a week-long course. We conclude from this experience that the
 235 hybrid approach has value but there may still be a better approach for future educational
 236 opportunities.

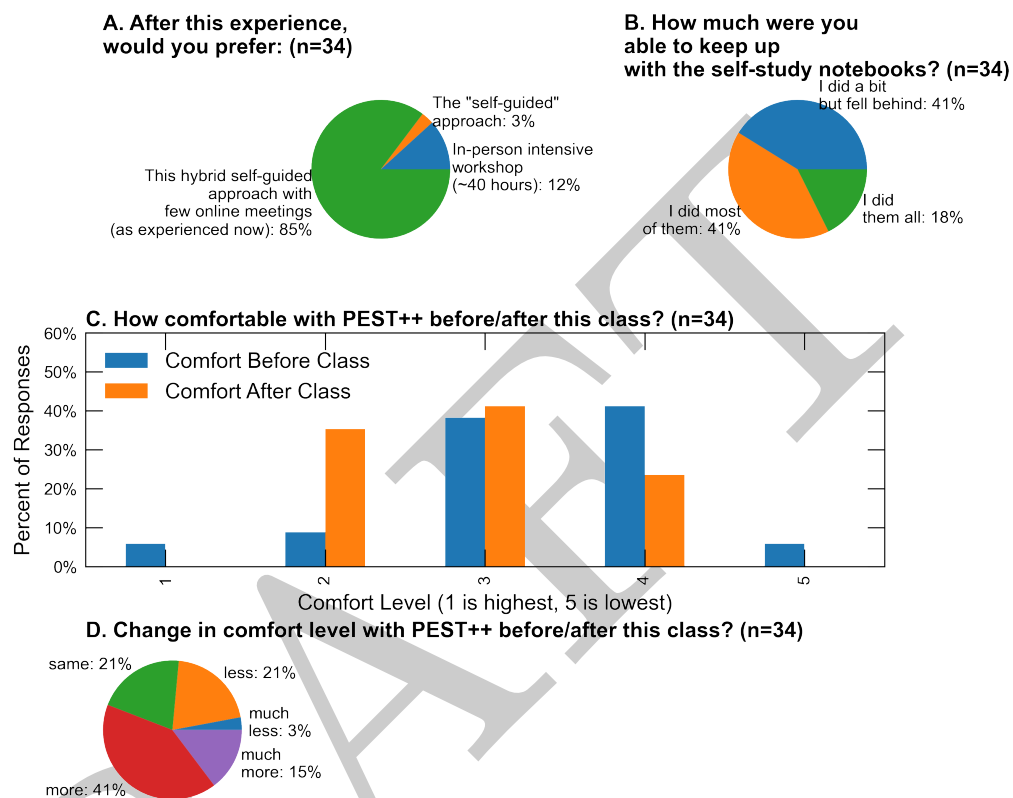


Figure 1: Summary of responses to post-course survey based on 34 responses. Panel A summarizes whether respondents would prefer and intensive in-person workshop or this hybrid option. Panel B summarizes how much of the notebooks respondents were able to complete throughout the course. Panel C summarizes respondent comfort level with PEST++ before and after the course. Panel D highlights individual changes in comfort level reported due to the course.

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 244 and contributions to the initial curriculum for this material and the early version of
 245 the notebooks. We finally thank users and stress-testers for their valuable feedback and
 246 continued community contributions to the repository.

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