

# <sup>1</sup> Connectome Mapper 3: A Flexible and Open-Source Pipeline Software for Multiscale Multimodal Human Connectome Mapping

<sup>4</sup> **Sebastien Tourbier<sup>1</sup>, Joan Rue-Queralt<sup>1</sup>, Katharina Glomb<sup>8</sup>, Yasser  
5 Aleman-Gomez<sup>1</sup>, Emeline Mullier<sup>1</sup>, Alessandra Griffa<sup>23</sup>, Mikkel  
6 Schöttner<sup>1</sup>, Jonathan Wirsich<sup>4</sup>, M. Anil Tuncel<sup>5</sup>, Jakub Jancovic<sup>6</sup>,  
7 Meritxell Bach Cuadra<sup>71</sup>, and Patric Hagmann<sup>1</sup>**

<sup>8</sup> 1 Radiology Department, Centre Hospitalier Universitaire Vaudois and University of Lausanne  
<sup>9</sup> (CHUV-UNIL), Switzerland <sup>2</sup> Department of Clinical Neurosciences, Division of Neurology, Geneva  
<sup>10</sup> University Hospitals and Faculty of Medicine, University of Geneva, Geneva, Switzerland <sup>3</sup> Institute of  
<sup>11</sup> Bioengineering, Center of Neuroprosthetics, École Polytechnique Fédérale De Lausanne (EPFL),  
<sup>12</sup> Geneva, Switzerland <sup>4</sup> EEG and Epilepsy Unit, University Hospitals and Faculty of Medicine of  
<sup>13</sup> Geneva, University of Geneva, Geneva, Switzerland <sup>5</sup> Blue Brain Project, École polytechnique fédérale  
<sup>14</sup> de Lausanne (EPFL), Campus Biotech, Geneva, Switzerland <sup>6</sup> Foxight, Geneva, Switzerland <sup>7</sup> CIBM  
<sup>15</sup> Center for Biomedical Imaging, Lausanne, Switzerland <sup>8</sup> Berlin Institute of Health at Charité;  
<sup>16</sup> Department of Neurology with Experimental Neurology, Brain Simulation Section, Charité  
<sup>17</sup> Universitätsmedizin Berlin, corporate member of Freie Universität Berlin and Humboldt-Universität zu  
<sup>18</sup> Berlin, Berlin, Germany

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

## Software

- [Review ↗](#)
- [Repository ↗](#)
- [Archive ↗](#)

---

Editor: Øystein Sørensen ↗

Reviewers:

- [@adbartni](#)
- [@jsheunis](#)

Submitted: 22 February 2022

Published: unpublished

## License

Authors of papers retain  
copyright and release the work  
under a Creative Commons  
Attribution 4.0 International  
License ([CC BY 4.0](#)).

## <sup>19</sup> Statement of Need

<sup>20</sup> The field of Magnetic Resonance Imaging (MRI) Connectomics has rapidly expanded since its  
<sup>21</sup> advent in the 2000s ([Sporns et al., 2005](#)), ([Hagmann, 2005](#)), ([Sporns & Bassett, 2018](#)). It has  
<sup>22</sup> revolutionized the way to investigate *in vivo*, *non-invasively* and *safely* at different macroscopic  
<sup>23</sup> scales the structural and functional systems of the brain by modeling connections between  
<sup>24</sup> brain areas as a graph or network, known as connectome, and has become a widely used set  
<sup>25</sup> of methods in Neuroscience ([Bassett & Sporns, 2017](#)). While brain areas are usually derived  
<sup>26</sup> from high resolution structural T1 weighted MRI (sMRI), structural brain connectomes are  
<sup>27</sup> mapped from diffusion MR imaging (dMRI) tractography, and functional brain connectomes are  
<sup>28</sup> usually mapped from resting-state functional MRI (rfMRI). Connectome Mapper (CMP), an  
<sup>29</sup> open-source pipeline software with a graphical user interface (GUI), was created to simplify the  
<sup>30</sup> organization, processing, and analysis of sMRI, dMRI, and rfMRI from raw data to multi-scale  
<sup>31</sup> structural weighted and functional connectomes ([Daducci et al., 2012](#)), using in a common  
<sup>32</sup> framework a multi-scale extension with hierarchical region grouping ([Cammoun et al., 2012](#))  
<sup>33</sup> of the Desikan-Killiany parcellation ([Desikan et al., 2006](#)).

<sup>34</sup> As MRI is being increasingly more accessible and used in both clinical and research settings,  
<sup>35</sup> such multi-modal MRI datasets are being gathered at an unprecedented rate. The size and  
<sup>36</sup> organization of these datasets as well as the increasing complexity of the processing pipelines to  
<sup>37</sup> analyze them present important challenges for scalable computing, data sharing, reproducibility  
<sup>38</sup> and transparency of the analysis. The last ten years have indeed witnessed a number of  
<sup>39</sup> technical advances and a trend towards the adoption of open research practices such as *open*  
<sup>40</sup> *data* and *open methods* ([Nichols et al., 2017](#)) ([Eglen et al., 2017](#)) ([Kennedy et al., 2019](#))  
<sup>41</sup> ([Poldrack et al., 2019](#)). This has led in particular to the creation of a community standard  
<sup>42</sup> for dataset organization, known as the Brain Imaging Data Structure (BIDS), designed to  
<sup>43</sup> ease the practice of sharing raw neuroimaging data ([Gorgolewski et al., 2016](#)). Combined with  
<sup>44</sup> advances in software virtualization, BIDS has enabled the creation of the BIDS Apps framework

which uses software container technology to encapsulate neuroimaging processing pipelines and ensures portability and reproducibility (Gorgolewski et al., 2017). A large ecosystem of processing pipelines supporting the mapping of connectomes has evolved around this framework. To the best of our knowledge, it includes C-PAC (Cameron et al., 2013), NIAK (Bellec, 2016), fMRIprep (Ghosh et al., 2018), dMRIprep (Richie-Halford et al., 2019), QSIPREP (Cieslak et al., 2021), MRtrix3\_connectome (Smith & Connelly, 2019), NDMG (Kiar et al., 2018) PyNets (Pisner & Hammonds, 2020), and Micapipe (Rodriguez-Cruces et al., 2022). All the existing solutions have demonstrated their capability in addressing the previously-mentioned challenges. However, none of them provide a direct alternative to CMP when dealing with multimodal datasets with the goal to create connectomes at multiple hierarchical scales.

Connectome Mapper 3 (CMP3) builds up on the two preceding versions of CMP and keeps the same philosophy. It introduces massive improvements in terms of the underlying codebase, the tools used, and the scope of the functionality provided. This includes the migration to Python 3, a revisited and extended multi-scale parcellation scheme, the adoption of the BIDS standard for data organization, the encapsulation of the processing pipelines in software container images, continuous testing in concordance to the BIDS Apps standard, and major upgrades of the diffusion and fMRI pipelines. Despite the recent emergence of electroencephalography (EEG) connectomics and the combination with the structural and functional connectome (Glomb, Mullier, et al., 2020) (Sadaghiani & Wirsich, 2020), no EEG pipeline exists to date. Initiated during OHBM BrainHack 2020 (<https://github.com/ohbm/hackathon2020/issues/214>), CMP3 is being extended to EEG. This manuscript summarizes CMP3 along with different design characteristics and principles.

## Summary

### A flexible and interoperable workflow for multi-modal human connectome mapping

Connectome Mapper 3 (CMP3) implements a workflow that creates a hierarchical multi-scale connectome representation of the structural and functional brain systems, from any sMRI / dMRI / rfMRI dataset structured according to the BIDS standard, as illustrated by Figure 1.

CMP3's workflow relies on Nipype (Gorgolewski et al., 2011) and adopts a modular architecture, composed of three different pipelines (anatomical, diffusion, and fMRI) dedicated to the processing of each modality (sMRI, dMRI, rfMRI). Each pipeline is represented by a Nipype workflow that takes a BIDS formatted dataset as input, and runs a number of sub-workflows (stages). Each stage can consist of one or multiple tasks, where each task can either interface with a specific tool of FSL (Jenkinson et al., 2012), FreeSurfer (Fischl, 2012), ANTs (Avants et al., 2008), dipy (Garyfallidis et al., 2014), mrtrix3 (Tournier et al., 2019), AFNI (Cox, 2012), or be fully implemented by CMP3 (Figure 1). We refer to the main documentation for more details about the different processing steps and parameters involved in each pipeline. At the time EEG is being fully integrated in the workflow and in the GUI, CMP3 already provides a pipeline dedicated to this modality with a collection of interfaces based on MNE-Python (Gramfort et al., 2013), MNE-Connectivity (Li et al., 2022), and PyCartool (Ferat, 2019). A tutorial notebook in the documentation shows how one can now map the connectivity at the source level derived from EEG in the CMP3 framework.

To guarantee consistent processing in large neuroimaging cohorts, pipeline and stage parameters can be set by creating and loading pipeline configuration files in .json format. Adopting BIDS allows CMP3 to automatically identify the structure of the input data, and to check the availability of sMRI, dMRI, rfMRI, and derived data. Depending on the input data, the processing pipelines and stages are then dynamically built and configured based on the parameters set in the different configuration files. Empowered by the Nipype workflow engine, the re-execution of the workflow will resume the processing at the stage where a change of parameter occurred, thus not needing to recompute outputs not affected by the change.

95 To ensure reproducibility and maximize re-usability of the tool, the implemented pipelines are  
 96 encapsulated in Docker (Merkel, 2014) and Singularity (Kurtzer et al., 2017) software image  
 97 containers, in concordance with the BIDS App framework (Gorgolewski et al., 2017). This  
 98 means that the BIDS App of CMP3 can be run on a large diversity of datasets, on Linux,  
 99 MacOSX, and Windows computers, and on high performance computing systems (clusters) for  
 100 large-scale analysis.

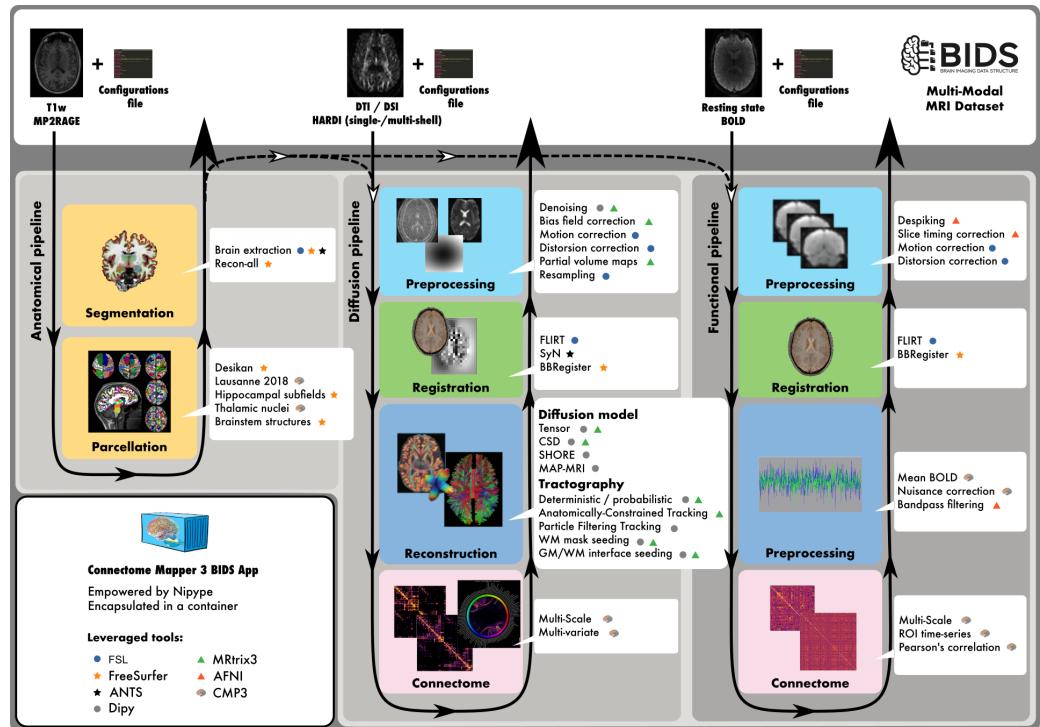
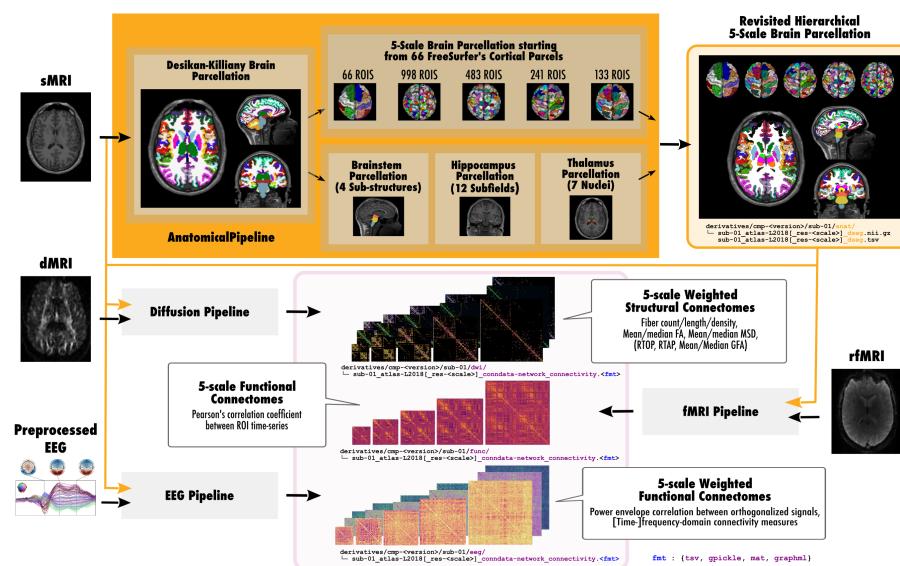


Figure 1: Overview of the Connectome Mapper 3 BIDS App's workflow.

101 All these design considerations make CMP3 easy to install and use (as it provides the user  
 102 with a computing environment in which the pipelines are guaranteed to run, and where all  
 103 dependencies are already installed), and this on a diversity of multi-modal BIDS datasets.  
 104 They also make CMP3 efficient in managing and scaling the pipeline execution while recording  
 105 provenance, and easy to customize and extend it for specific needs.

## 106 A revisited and extended multi-scale cortical parcellation scheme

107 CMP3 revisits the multiscale cortical parcellation proposed by (Cammoun et al., 2012). The  
 108 parcellation derived from the Desikan-Killiany atlas (Desikan et al., 2006) has been made  
 109 symmetric by projecting the right hemisphere labels to the left hemisphere, matching the  
 110 boundaries of the projected regions of the left hemisphere to the boundaries of the original  
 111 regions of the left hemisphere, applying this transformation to the rest of the scales, and  
 112 saving each parcellation scale of each hemisphere in a Freesurfer annotation file. It also  
 113 extends the parcellations with new structures including a subdivision of the thalamus into  
 114 7 nuclei per hemisphere, of the hippocampus into 12 subfields, and of the brainstem into 4  
 115 sub-structures. An overview and brief description of the new scheme and its integration with  
 116 all the implemented pipelines are provided in Figure 2.



**Figure 2: Overview of the new multi-scale parcellation scheme.** After performing Desikan-Killiany brain parcellation (Desikan et al., 2006) with Freesurfer, CMP3 resamples the fsaverage cortical surface onto the individual cortical surface and maps the parcellation annotation files to the individual space, to generate the volumetric parcellation for each scale. Then, one can now decide whether to perform brainstem parcellation (Iglesias, Van Leemput, et al., 2015), hippocampal subfields segmentation (Iglesias, Augustinack, et al., 2015), and/or probabilistic atlas-based segmentation of the thalamic nuclei (Najdenovska et al., 2018). All segmented structures are then combined to create the final parcellation nifti image at each scale along with the corresponding label index color mapping file in accordance with the BIDS Derivatives specifications. The different segmentation and parcellation outputs of the anatomical pipeline are then taken as inputs of the diffusion, fMRI, and EEG pipelines that estimate the structural and functional connectomes from raw dMRI, raw rfMRI, and preprocessed EEG data and the pairs of sub-cortical and cortical areas previously segmented. All connectome files employ a common naming convention, based on the current BIDS extension proposal (BEP) 17 for generic BIDS connectivity data schema, and can be saved in a diversity of formats (tsv, gpickle, mat, graphml) compatible with the most popular software packages used in this field to perform complex network analyses (See next section for more details).

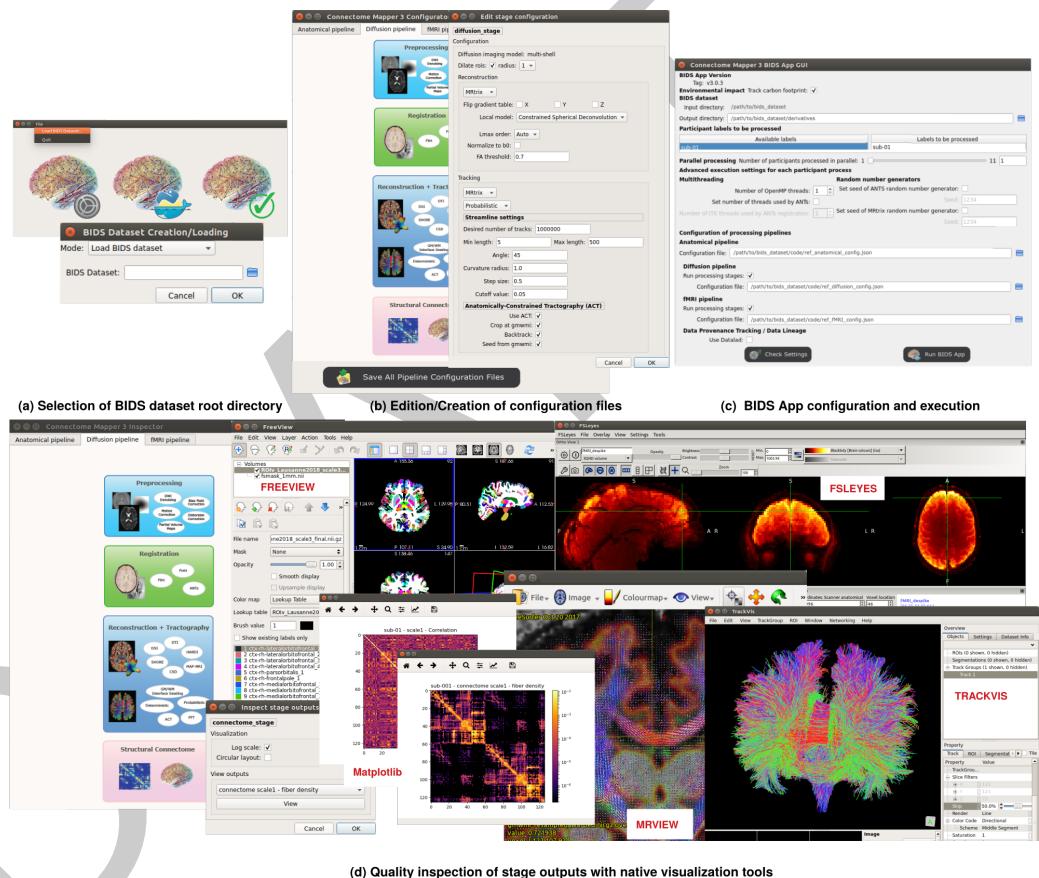
## 117 Outputs ready to be reused in the BIDS ecosystem

118 CMP3 outputs follow the BIDS Derivatives specifications wherever possible, which facilitates  
 119 the sharing of the derivatives in the BIDS App ecosystem, and allows the user to easily retrieve  
 120 any of the files generated by CMP3 with tools of the BIDS ecosystem such as pybids (Yarkoni et  
 121 al., 2019). It introduces a new BIDS entity `atlas-<atlas_label>` (See [proposal](#)) that is used  
 122 in combination with the `res-<atlas_scale>` entity to distinguish imaging and network data  
 123 derived from different parcellation atlases and scales (Figure 2). While the BIDS-Derivatives  
 124 extension to organize network data (See [BEP017](#)) is being developed, in which we are actively  
 125 participating, structural and functional connectome files derived from the different imaging  
 126 modalities are saved in multiple formats following the convention shown in [Figure 2](#). All  
 127 connectomes are saved by default as graph edge lists in .tsv files, that can be directly analyzed  
 128 using [NetworkX](#) (Hagberg et al., 2008), a Python library which offers many algorithms and  
 129 tools to explore graphs and compute local and global network properties. Connectivity matrices  
 130 can be exported to Matlab as MAT-files can be fed to the [Brain Connectivity Toolbox](#) (Rubinov  
 131 & Sporns, 2010), which is a powerful toolbox containing a large selection of network measures  
 132 for the characterization of brain connectivity datasets. Finally, connectomes can be saved in  
 133 GraphML format to interface with a lot of general purpose software packages for graph analysis  
 134 such as [Cytoscape](#) (Shannon et al., 2003) ([Gustavsen et al., 2019](#)) or [Gephi](#) (Bastian et al.,  
 135 2009). Structuring outputs as BIDS Derivatives and saving them in a range of file formats

thus has a lot of advantages. Not only does it ensure that the connectome files can be opened by the most popular software packages used in this field to perform complex network analyses, but it also eases the reuse of all outputs in the BIDS ecosystem.

### 139 A focus on accessibility and versatility

140 CMP3 takes advantage of the Traits/TraitsUI framework (<http://docs.enthought.com/traits/>)  
 141 for building an interactive GUI, to give to pipelines and stages a graphical representation which  
 142 is easy to understand and extend. This has enabled the design of a GUI, which we call the  
 143 `cmpbidsappmanager`, that reflects the modular structure of the processing workflow. It has  
 144 been designed to guide and support the user in all the steps required to perform an analysis  
 145 (Figure 3).



**Figure 3: Graphical User Interface of the Connectome Mapper 3.** A typical procedure to perform an analysis would consist of (a) the selection of the root directory of the BIDS dataset to be analyzed, (b) the creation/editation of the different pipeline configuration files, (c) the configuration of the BIDS App run and its execution, and (d) the inspection of stage outputs with fsleyes, freeview, mrview, or TrackVis depending on the tool involved in the stage.

146 Each pipeline can be individually configured and executed with the aid of the user-friendly GUI  
 147 and the output of each stage can be visually reviewed, enabling the user to keep an eye on  
 148 the data being processed, change the parameters and re-execute the pipeline when it is found  
 149 not to be satisfactory. In this way, CMP3 simplifies the creation of connectomes and makes  
 150 it a straightforward process even for users not familiar with Nipype and software container  
 151 technology. Nevertheless, it still fulfills the needs of advanced users in charge of analyzing large  
 152 datasets. It offers them the possibility to tune and save all the parameters in configuration files,

153 which can then be employed for running the BIDS App either with the Docker or Singularity  
154 software container engine directly, or with the two [lightweight Docker and Singularity wrappers](#).

### 155 Developed with open science in mind

156 CMP3 is published under the terms of the open source 3-Clause Berkeley Software Distribution  
157 (3-Clause BSD) license, which allows unlimited modification, redistribution and commercial  
158 use in source and binary forms, as long as the copyright notice is retained and the license's  
159 disclaimers of warranty are maintained. The source code for CMP3 is hosted at <https://github.com/connectomicslab/connectomemapper3>, where all bugs and contributions are  
160 transparently discussed and managed through issues, and each release is published to the  
161 [Python Package Index \(PyPI\)](#) and archived to Zenodo ([Tourbier et al., 2022](#)). In case of  
162 problems, CMP3 has a dedicated forum at [groups.google.com/group/cmtk-users](https://groups.google.com/group/cmtk-users) where a  
163 community of users is active to support each other and have scientific discussions. To be  
164 robust to adverse code changes, versions are released through continuous integration building  
165 and testing. Specifically, this involves testing the installation of the python package, the  
166 build of the Docker and Singularity container images, the execution of the BIDS App via the  
167 different container images adopting multiple pipeline configurations, using a sample multi-  
168 modal MRI dataset ([Tourbier & Hagmann, 2020](#)) that has been created for this purpose,  
169 the publication of the new version of the Python package to PyPI, and the deployment of  
170 the container images to [DockerHub](#) and [Sylabs Cloud](#). Doing so, we can guarantee the  
171 full functionality of each newly released version of CMP3 for a range of different use cases.  
172 More details about CMP3, the different processing steps and generated outputs together  
173 with installation and usage instructions, different tutorials supporting the analysis, and the  
174 interpretation of the generated outputs with popular tools, can be found in the documentation  
175 ([connectome-mapper-3.readthedocs.io](#)) that is kept up to date with the current release and  
176 can be retrieved for older versions.

### 178 Mention

179 CMP3 has been successfully employed in a number of methodological ([Zheng et al., 2020](#))  
180 ([Glomb, Rué Queralt, et al., 2020](#)) ([Glomb, Mullier, et al., 2020](#)) ([Akselrod et al., 2021](#)) ([Rué-  
181 Queralt et al., 2021](#)) ([Pascucci et al., 2021](#)), clinical ([Carboni et al., 2019](#)) ([Vorderwülbecke  
182 et al., 2020](#)) ([Carboni et al., 2020](#)) ([Carboni et al., 2022](#)), and data ([Pascucci et al., 2022a](#))  
183 ([Pascucci et al., 2022b](#)) research articles. CMP3 is part of the [BIDS Apps](#), and also part  
184 of [ReproNim/containers](#), a Datalad dataset with a collection of 40 popular containerized  
185 neuroimaging research pipelines, which allows one to easily include it as a subdataset within  
186 Datalad-controlled BIDS datasets, and achieve fully reproducible analysis by running CMP3  
187 directly with Datalad.

### 188 Acknowledgements

189 This work was supported by Swiss National Science Foundation Sinergia [grant no. 170873](#).  
190 Katharina Glomb's involvement was also supported by DFG Priority Program "SPP DBS RI  
191 2073/10-2". M. Anil Tuncel's involvement was supported by funding to the Blue Brain Project,  
192 a research center of the École polytechnique fédérale de Lausanne (EPFL), from the Swiss  
193 government's ETH Board of the Swiss Federal Institutes of Technology. All the contributors  
194 listed in the project's Zenodo and GitHub repository have contributed code and intellectual  
195 labor to further improve CMP3.

## 196 References

- 197 Akselrod, M., Martuzzi, R., Zwaag, W. van der, Blanke, O., & Serino, A. (2021). Relation  
198 between palm and finger cortical representations in primary somatosensory cortex: A 7T  
199 fMRI study. *Human Brain Mapping*, 42(7), 2262–2277. <https://doi.org/10.1002/hbm.25365>
- 200
- 201 Avants, B., Epstein, C., Grossman, M., & Gee, J. (2008). Symmetric diffeomorphic image  
202 registration with cross-correlation: Evaluating automated labeling of elderly and neurode-  
203 generative brain. *Medical Image Analysis*, 12(1), 26–41. <https://doi.org/10.1016/j.media.2007.06.004>
- 204
- 205 Bassett, D. S., & Sporns, O. (2017). Network neuroscience. *Nature Neuroscience*, 20(3),  
206 353–364. <https://doi.org/10.1038/nn.4502>
- 207
- 208 Bastian, M., Heymann, S., & Jacomy, M. (2009). *Gephi: An open source software for exploring  
209 and manipulating networks*. <http://www.aaai.org/ocs/index.php/ICWSM/09/paper/view/154>
- 210
- 211 Bellec, P. (2016). *Neuroimaging Analysis Kit - Progress and challenges for standardized fMRI  
212 processing*. [https://www.mcgill.ca/bic/files/bic/2016\\_10-17\\_-\\_neuroimage\\_analysis\\_-  
kit\\_-\\_pierre\\_bellec.pdf](https://www.mcgill.ca/bic/files/bic/2016_10-17_-_neuroimage_analysis_-<br/>kit_-_pierre_bellec.pdf)
- 212
- 213 Cameron, C., Sharad, S., Brian, C., Ranjeet, K., Satrajit, G., Chaogan, Y., Qingyang, L., Daniel,  
214 L., Joshua, V., Randal, B., Stanley, C., Maarten, M., Clare, K., Adriana, D. M., Francisco,  
215 C., & Michael, M. (2013). Towards Automated Analysis of Connectomes: The Configurable  
216 Pipeline for the Analysis of Connectomes (C-PAC). *Frontiers in Neuroinformatics*, 7(42).  
217 <https://doi.org/10.3389/conf.fninf.2013.09.00042>
- 218
- 219 Cammoun, L., Gigandet, X., Meskaldji, D., Thiran, J. P., Sporns, O., Do, K. Q., Maeder, P.,  
220 Meuli, R., & Hagmann, P. (2012). Mapping the human connectome at multiple scales  
221 with diffusion spectrum MRI. *Journal of Neuroscience Methods*. <https://doi.org/10.1016/j.jneumeth.2011.09.031>
- 222
- 223 Carboni, M., Brunet, D., Seeber, M., Michel, C. M., Vulliemoz, S., & Vorderwülbecke, B. J.  
224 (2022). Linear distributed inverse solutions for interictal EEG source localisation. *Clinical  
Neurophysiology*, 133, 58–67. <https://doi.org/10.1016/j.clinph.2021.10.008>
- 225
- 226 Carboni, M., De Stefano, P., Vorderwülbecke, B. J., Tourbier, S., Mullier, E., Rubega, M.,  
227 Momjian, S., Schaller, K., Hagmann, P., Seeck, M., Michel, C. M., van Mierlo, P., &  
228 Vulliemoz, S. (2020). Abnormal directed connectivity of resting state networks in focal  
epilepsy. *NeuroImage: Clinical*, 27, 102336. <https://doi.org/10.1016/j.nicl.2020.102336>
- 229
- 230 Carboni, M., Rubega, M., Iannotti, G. R., De Stefano, P., Toscano, G., Tourbier, S., Pittau,  
231 F., Hagmann, P., Momjian, S., Schaller, K., Seeck, M., Michel, C. M., van Mierlo, P., &  
232 Vulliemoz, S. (2019). The network integration of epileptic activity in relation to surgical  
233 outcome. *Clinical Neurophysiology*, 130(12), 2193–2202. <https://doi.org/10.1016/j.clinph.2019.09.006>
- 234
- 235 Cieslak, M., Cook, P. A., He, X., Yeh, F.-C., Dhollander, T., Adebimpe, A., Aguirre, G. K.,  
236 Bassett, D. S., Betzel, R. F., Bourque, J., Cabral, L. M., Davatzikos, C., Detre, J. A., Earl,  
237 Elliott, M. A., Fadnavis, S., Fair, D. A., Foran, W., Fotiadis, P., ... Satterthwaite, T. D.  
238 (2021). QSIPrep: an integrative platform for preprocessing and reconstructing diffusion MRI  
data. *Nature Methods*, 18(7), 775–778. <https://doi.org/10.1038/s41592-021-01185-5>
- 239
- 240 Cox, R. W. (2012). AFNI: What a long strange trip it's been. *NeuroImage*, 62(2), 743–747.  
<https://doi.org/10.1016/J.NEUROIMAGE.2011.08.056>
- 241
- 242 Daducci, A., Gerhard, S., Griffa, A., Lemkadem, A., Cammoun, L., Gigandet, X., Meuli,  
R., Hagmann, P., & Thiran, J. P. (2012). The Connectome Mapper: An Open-Source

- 243 Processing Pipeline to Map Connectomes with MRI. *PLoS ONE*, 7(12). <https://doi.org/10.1371/journal.pone.0048121>
- 244
- 245 Desikan, R. S., Ségonne, F., Fischl, B., Quinn, B. T., Dickerson, B. C., Blacker, D., Buckner, R. L., Dale, A. M., Maguire, R. P., Hyman, B. T., Albert, M. S., & Killiany, R. J. (2006). An automated labeling system for subdividing the human cerebral cortex on MRI scans into gyral based regions of interest. *NeuroImage*, 31(3), 968–980. <https://doi.org/10.1016/j.neuroimage.2006.01.021>
- 246
- 247
- 248
- 249
- 250 Eglen, S. J., Marwick, B., Halchenko, Y. O., Hanke, M., Sufi, S., Gleeson, P., Silver, R. A., Davison, A. P., Lanyon, L., Abrams, M., Wachtler, T., Willshaw, D. J., Pouzat, C., & Poline, J. B. (2017). Toward standard practices for sharing computer code and programs in neuroscience. *Nature Neuroscience*, 20(6), 770–773. <https://doi.org/10.1038/nn.4550>
- 251
- 252
- 253
- 254 Ferat, V. (2019). *PyCartool: A simple open source Python package for I/O between Cartool and python* (Version 0.1.1) [Computer software]. <https://github.com/Functional-Brain-Mapping-Laboratory/PyCartool>
- 255
- 256
- 257 Fischl, B. (2012). FreeSurfer. *NeuroImage*, 62(2), 774–781. <https://doi.org/10.1016/j.neuroimage.2012.01.021>
- 258
- 259 Garyfallidis, E., Brett, M., Amirbekian, B., Rokem, A., Walt, S. van der, Descoteaux, M., & Nimmo-Smith, I. (2014). Dipy, a library for the analysis of diffusion MRI data. *Frontiers in Neuroinformatics*, 8(FEB), 1–17. <https://doi.org/10.3389/fninf.2014.00008>
- 260
- 261
- 262 Ghosh, S. S., Kent, J. D., Erramuzpe, A., DuPre, E., Snyder, M., Blair, R. W., Moodie, C. A., Esteban, O., Duriez, J., Isik, A. I., Poldrack, R. A., Goncalves, M., Wright, J., Oya, H., Gorgolewski, K. J., & Markiewicz, C. J. (2018). fMRIprep: a robust preprocessing pipeline for functional MRI. *Nature Methods*, 16(1), 111–116. <https://doi.org/10.1038/s41592-018-0235-4>
- 263
- 264
- 265
- 266
- 267 Glomb, K., Mullier, E., Carboni, M., Rubega, M., Iannotti, G., Tourbier, S., Seeber, M., Vulliemoz, S., & Hagmann, P. (2020). Using structural connectivity to augment community structure in EEG functional connectivity. *Network Neuroscience*, 4(3), 761–787. [https://doi.org/10.1162/netn\\_a\\_00147](https://doi.org/10.1162/netn_a_00147)
- 268
- 269
- 270
- 271 Glomb, K., Rué Queralt, J., Pascucci, D., Defferrard, M., Tourbier, S., Carboni, M., Rubega, M., Vulliémoz, S., Plomp, G., & Hagmann, S. (2020). Connectome spectral analysis to track EEG task dynamics on a subsecond scale. *NeuroImage*, 221, 117137. <https://doi.org/10.1016/j.neuroimage.2020.117137>
- 272
- 273
- 274
- 275 Gorgolewski, K. J., Alfaro-Almagro, F., Auer, T., Bellec, P., Capotă, M., Chakravarty, M. M., Churchill, N. W., Cohen, A. L., Craddock, R. C., Devenyi, G. A., Eklund, A., Esteban, O., Flandin, G., Ghosh, S. S., Guntupalli, J. S., Jenkinson, M., Keshavan, A., Kiar, G., Liem, F., ... Poldrack, R. A. (2017). BIDS apps: Improving ease of use, accessibility, and reproducibility of neuroimaging data analysis methods. *PLOS Computational Biology*, 13(3), e1005209. <https://doi.org/10.1371/journal.pcbi.1005209>
- 276
- 277
- 278
- 279
- 280
- 281 Gorgolewski, K. J., Auer, T., Calhoun, V. D., Craddock, R. C., Das, S., Duff, E. P., Flandin, G., Ghosh, S. S., Glatard, T., Halchenko, Y. O., Handwerker, D. A., Hanke, M., Keator, D., Li, X., Michael, Z., Maumet, C., Nichols, B. N., Nichols, T. E., Pellman, J., ... Poldrack, R. A. (2016). The brain imaging data structure, a format for organizing and describing outputs of neuroimaging experiments. *Scientific Data*, 3, 1–9. <https://doi.org/10.1038/sdata.2016.44>
- 282
- 283
- 284
- 285
- 286 Gorgolewski, K. J., Burns, C. D., Madison, C., Clark, D., Halchenko, Y. O., Waskom, M. L., & Ghosh, S. S. (2011). Nipype: A Flexible, Lightweight and Extensible Neuroimaging Data Processing Framework in Python. *Frontiers in Neuroinformatics*, 5(August). <https://doi.org/10.3389/fninf.2011.00013>
- 287
- 288
- 289
- 290 Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C., Goj, R., Jas, M., Brooks, T., Parkkonen, L., & Hämäläinen, M. S. (2013). MEG and
- 291

- 292        EEG data analysis with MNE-Python. *Frontiers in Neuroscience*, 7(267), 1–13. <https://doi.org/10.3389/fnins.2013.00267>
- 293
- 294        Gustavsen, A., J., Pai, Shraddha, Isserlin, Ruth, Demchak, Barry, Pico, & R., A. (2019). RCy3:  
295        Network biology using cytoscape from within r. *F1000Research*. <https://doi.org/10.12688/f1000research.20887.3>
- 296
- 297        Hagberg, A. A., Schult, D. A., & Swart, P. J. (2008). Exploring network structure, dynamics,  
298        and function using NetworkX. In G. Varoquaux, T. Vaught, & J. Millman (Eds.), *Proceedings of the 7th python in science conference* (pp. 11–15). [http://conference.scipy.org/proceedings/SciPy2008/paper\\_2/](http://conference.scipy.org/proceedings/SciPy2008/paper_2/)
- 299
- 300
- 301        Hagmann, P. (2005). *From diffusion MRI to brain connectomics* (Vol. 3230) [PhD thesis,  
302        EPFL]. <https://doi.org/10.5075/epfl-thesis-3230>
- 303
- 304        Iglesias, J. E., Augustinack, J. C., Nguyen, K., Player, C. M., Player, A., Wright, M., Roy,  
305        N., Frosch, M. P., McKee, A. C., Wald, L. L., Fischl, B., & Van Leemput, K. (2015).  
306        A computational atlas of the hippocampal formation using ex vivo, ultra-high resolution  
307        MRI: Application to adaptive segmentation of in vivo MRI. *NeuroImage*, 115, 117–137.  
<https://doi.org/10.1016/j.neuroimage.2015.04.042>
- 308
- 309        Iglesias, J. E., Van Leemput, K., Bhatt, P., Casillas, C., Dutt, S., Schuff, N., Truran-Sacrey,  
310        D., Boxer, A., & Fischl, B. (2015). Bayesian segmentation of brainstem structures in MRI.  
*NeuroImage*, 113, 184–195. <https://doi.org/10.1016/j.neuroimage.2015.02.065>
- 311
- 312        Jenkinson, M., Beckmann, C. F., Behrens, T. E. J., Woolrich, M. W., & Smith, S. M. (2012).  
313        FSL. *NeuroImage*, 62(2), 782–790. <https://doi.org/10.1016/J.NEUROIMAGE.2011.09.015>
- 314
- 315        Kennedy, D. N., Abraham, S. A., Bates, J. F., Crowley, A., Ghosh, S., Gillespie, T., Goncalves,  
316        M., Grethe, J. S., Halchenko, Y. O., Hanke, M., Haselgrove, C., Hodge, S. M., Jarecka, D.,  
317        Kaczmarzyk, J., Keator, D. B., Meyer, K., Martone, M. E., Padhy, S., Poline, J., ... Travers,  
318        M. (2019). Everything Matters: The ReproNim Perspective on Reproducible Neuroimaging.  
*Frontiers in Neuroinformatics*, 13(February), 1–9. <https://doi.org/10.3389/fninf.2019.00001>
- 319
- 320        Kiar, G., Bridgeford, E., Roncal, W. G., (CoRR), C. for R., Reproducibility, Chandrashekhar,  
321        V., Mhembere, D., Ryman, S., Zuo, X.-N., Marguiles, D. S., Craddock, R. C., Priebe, C.  
322        E., Jung, R., Calhoun, V., Caffo, B., Burns, R., Milham, M. P., & Vogelstein, J. (2018).  
323        A High-Throughput Pipeline Identifies Robust Connectomes But Troublesome Variability.  
*bioRxiv*, 188706. <https://doi.org/10.1101/188706>
- 324
- 325        Kurtzer, G. M., Sochat, V., & Bauer, M. W. (2017). Singularity: Scientific containers for  
326        mobility of compute. *PLOS ONE*, 12(5), e0177459. <https://doi.org/10.1371/journal.pone.0177459>
- 327
- 328        Li, A., McCloy, D., Larson, E., Westner, B., Kroner, A., & Gramfort, A. (2022). *mne-connectivity* (Version 0.2.0) [Computer software]. <https://github.com/mne-tools/mne-connectivity>
- 329
- 330
- 331        Merkel, D. (2014). Docker: Lightweight linux containers for consistent development and  
332        deployment. *Linux Journal*, 2014(239), 2.
- 333
- 334        Najdenovska, E., Alemán-Gómez, Y., Battistella, G., Descoteaux, M., Hagmann, P., Jacquemont,  
335        S., Maeder, P., Thiran, J. P., Fornari, E., & Cuadra, M. B. (2018). In-vivo probabilistic  
336        atlas of human thalamic nuclei based on diffusion-weighted magnetic resonance  
337        imaging. *Scientific Data*, 5(November), 1–11. <https://doi.org/10.1038/sdata.2018.270>
- 338
- 339        Nichols, T. E., Das, S., Eickhoff, S. B., Evans, A. C., Glatard, T., Hanke, M., Kriegeskorte,  
340        N., Milham, M. P., Poldrack, R. A., Poline, J. B., Proal, E., Thirion, B., Van Essen, D.

- 339 C., White, T., & Yeo, B. T. T. (2017). *Best practices in data analysis and sharing in*  
340 *neuroimaging using MRI* (No. 3; Vol. 20, pp. 299–303). <https://doi.org/10.1038/nrn.4500>
- 341 Pascucci, D., Rubega, M., Rué-Queralt, J., Tourbier, S., Hagmann, P., & Plomp, G. (2021).  
342 Structure supports function: Informing directed and dynamic functional connectivity with  
343 anatomical priors. *Network Neuroscience*, 1–37. [https://doi.org/10.1162/netn\\_a\\_00218](https://doi.org/10.1162/netn_a_00218)
- 344 Pascucci, D., Tourbier, S., Rué-Queralt, J., Carboni, M., Hagmann, P., & Plomp, G. (2022a).  
345 Source imaging of high-density visual evoked potentials with multi-scale brain parcellations  
346 and connectomes. *Scientific Data*, 9(1), 9. <https://doi.org/10.1038/s41597-021-01116-1>
- 347 Pascucci, D., Tourbier, S., Rué-Queralt, J., Carboni, M., Hagmann, P., & Plomp, G. (2022b).  
348 “VEPCON: Source imaging of high-density visual evoked potentials with multi-scale brain  
349 parcellations and connectomes” [Data set]. OpenNeuro. <https://doi.org/doi:10.18112/openneuro.ds003505.v1.1.1>
- 350 Pisner, D., & Hammonds, R. (2020). PyNets: A Reproducible Workflow for Structural and  
351 Functional Connectome Ensemble Learning. *26th Annual Meeting of the Organization for*  
352 *Human Brain Mapping*.
- 353 Poldrack, R. A., Gorgolewski, K. J., & Varoquaux, G. (2019). Computational and Informatic  
354 Advances for Reproducible Data Analysis in Neuroimaging. *Annual Review of Biomedical*  
355 *Data Science*, 2(1), 119–138. <https://doi.org/10.1146/annurev-biodatasci-072018-021237>
- 356 Richie-Halford, A., Keshavan, A., Joseph, M., Lerma-Usabiaga, G., Pisner, D., Rokem, A.,  
357 & Esteban, O. (2019). *dMRIPrep: a robust preprocessing pipeline for diffusion MRI*.  
358 <https://doi.org/10.5281/zenodo.3571874>
- 359 Rodriguez-Cruces, R., Royer, J., Herholz, P., Lariviere, S., Vos de Wael, R., Paquola, C.,  
360 Benkarim, O., Park, B., Degre-Pelletier, J., Nelson, M., DeKraker, J., Tardif, C., Poline, J.-  
361 B., Concha, L., & Bernhardt, B. (2022). Micapipe: A pipeline for multimodal neuroimaging  
362 and connectome analysis. *bioRxiv*. <https://doi.org/10.1101/2022.01.31.478189>
- 363 Rubinov, M., & Sporns, O. (2010). Complex network measures of brain connectivity: Uses and  
364 interpretations. *NeuroImage*, 52(3), 1059–1069. <https://doi.org/10.1016/j.neuroimage.2009.10.003>
- 365 Rué-Queralt, J., Glomb, K., Pascucci, D., Tourbier, S., Carboni, M., Vulliémoz, S., Plomp,  
366 G., & Hagmann, P. (2021). The connectome spectrum as a canonical basis for a sparse  
367 representation of fast brain activity. *NeuroImage*, 244, 118611. <https://doi.org/10.1016/j.neuroimage.2021.118611>
- 368 Sadaghiani, S., & Wirsich, J. (2020). Intrinsic connectome organization across temporal  
369 scales: New insights from cross-modal approaches. *Network Neuroscience*, 4(1), 1–29.  
370 [https://doi.org/10.1162/netn\\_a\\_00114](https://doi.org/10.1162/netn_a_00114)
- 371 Shannon, P., Markiel, A., Ozier, O., Baliga, N. S., Wang, J. T., Ramage, D., Amin, N.,  
372 Schwikowski, B., & Ideker, T. (2003). Cytoscape: A software environment for integrated  
373 models of biomolecular interaction networks. *Genome Research*, 13(11), 2498–2504.  
374 <https://doi.org/10.1101/gr.123930>
- 375 Smith, R. E., & Connelly, A. (2019). A BIDS Application for quantitative structural connectome  
376 construction. *OHBM Annual Meeting*.
- 377 Sporns, O., & Bassett, D. S. (2018). Editorial: New Trends in Connectomics. *Network*  
378 *Neuroscience*, 2(2), 125–127. [https://doi.org/10.1162/netn\\_e\\_00052](https://doi.org/10.1162/netn_e_00052)
- 379 Sporns, O., Tononi, G., & Kötter, R. (2005). The human connectome: A structural description  
380 of the human brain. *PLoS Computational Biology*, 1(4), 0245–0251. <https://doi.org/10.1371/journal.pcbi.0010042>
- 381
- 382
- 383
- 384

- 385 Tourbier, S., Aleman-Gomez, Y., Mullier, E., Griffa, A., Bach Cuadra, M., & Hagmann,  
386 P. (2022). *connectomicslab/connectomemapper3: Connectome Mapper v3.0.3* (Version  
387 v3.0.3) [Computer software]. Zenodo. <https://doi.org/10.5281/zenodo.3475969>
- 388 Tourbier, S., & Hagmann, P. (2020). *Sample Multi-Modal BIDS dataset*. <https://doi.org/10.5281/ZENODO.3712762>
- 389 Tournier, J.-D., Smith, R., Raffelt, D., Tabbara, R., Dhollander, T., Pietsch, M., Christiaens,  
390 D., Jeurissen, B., Yeh, C.-H., & Connelly, A. (2019). MRtrix3: A fast, flexible and open  
391 software framework for medical image processing and visualisation. *NeuroImage*, 202,  
392 116137. <https://doi.org/10.1016/j.neuroimage.2019.116137>
- 393 Vorderwülbecke, B. J., Carboni, M., Tourbier, S., Brunet, D., Seeber, M., Spinelli, L., Seeck,  
394 M., & Vulliemoz, S. (2020). High-density Electric Source Imaging of interictal epileptic  
395 discharges: How many electrodes and which time point? *Clinical Neurophysiology*, 131(12).  
396 <https://doi.org/10.1016/j.clinph.2020.09.018>
- 397 Yarkoni, T., Markiewicz, C. J., Vega, A. de la, Gorgolewski, K. J., Salo, T., Halchenko, Y. O.,  
398 McNamara, Q., DeStasio, K., Poline, J.-B., Petrov, D., Hayot-Sasson, V., Nielson, D. M.,  
399 Carlin, J., Kiar, G., Whitaker, K., DuPre, E., Wagner, A., Tirrell, L. S., Jas, M., ... Blair,  
400 R. (2019). PyBIDS: Python tools for BIDS datasets. *Journal of Open Source Software*,  
401 4(40), 1294. <https://doi.org/10.21105/joss.01294>
- 402 Zheng, M., Allard, A., Hagmann, P., Aleman-Gómez, Y., & Serrano, M. Á. (2020). Geometric  
403 renormalization unravels self-similarity of the multiscale human connectome. *Proceedings  
404 of the National Academy of Sciences*, 117(33), 20244–20253. <https://doi.org/10.1073/PNAS.1922248117>
- 405
- 406