

# <sup>1</sup> pyfive: A pure-Python HDF5 reader

<sup>2</sup> **Bryan N. Lawrence**  <sup>1,2</sup>, **Ezequiel Cimadevilla**  <sup>3</sup>, **Wout De Nolf**  <sup>4</sup>, **David Hassell**  <sup>1,2</sup>, **Jonathan Helmus**<sup>1</sup>, **Brian Maranville**  <sup>5</sup>, **Benjamin Hodel**<sup>1</sup>, **Kai Mühlbauer**  <sup>6</sup>, and **Valeriu Predoi**  <sup>1,2</sup>

<sup>5</sup> **1** National Center for Atmospheric Science (NCAS), United Kingdom.  <sup>2</sup> Department of Meteorology, University of Reading, Reading, United Kingdom.  <sup>3</sup> Instituto de Física de Cantabria (IFCA), CSIC-Universidad de Cantabria, Santander, Spain. <sup>4</sup> European Synchrotron Radiation Facility (ESRF), Grenoble, France. <sup>5</sup> NIST Center for Neutron Research <sup>6</sup> Institute of Geosciences, Meteorology Section, University of Bonn, Germany.

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

## Software

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

---

Editor: [Open Journals](#) ↗

## Reviewers:

- [@openjournals](#)

Submitted: 01 January 1970

Published: unpublished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>21</sup>

## <sup>10</sup> Summary

<sup>11</sup> pyfive (<https://pyfive.readthedocs.io/en/latest/>) is an open-source thread-safe pure Python package for reading data stored in HDF5. While it is not a complete implementation of all the specifications and capabilities of HDF5, it includes all the core functionality necessary to read gridded datasets, whether stored contiguously or with chunks, and to carry out the necessary decompression for the standard options. All data access is fully lazy, the data is only read from storage when the numpy data arrays are manipulated. Originally developed some years ago, the package has recently been upgraded to support lazy access, and to add missing features necessary for handling all the environmental data known to the authors. It is now a realistic option for production data access in environmental science and more widely. The API is based on that of h5py (which is a Python shimmy over the HDF5 C-library, and hence is not thread-safe), with some API extensions to help optimise remote access. With these extensions, coupled with thread safety, many of the limitations precluding the efficient use of HDF5 (and netCDF4) on cloud storage have been removed.<sup>22</sup>

## <sup>24</sup> Statement of need

<sup>25</sup> HDF5<sup>1</sup> ([Folk et al., 2011](#)) is probably the most important data format in physical science, used across the piste. It is particularly important in environmental science, particularly given the fact that netCDF4<sup>2</sup> ([Rew et al., 2006](#)) is HDF5 under the hood. From satellite missions, to climate models and radar systems, the default binary format has been HDF5 for decades. While newer formats are starting to get mindshare, there are petabytes, if not exabytes, of existing HDF5, and there are still many good use-cases for creating new data in HDF5. However, despite the history, there are few libraries for reading HDF5 file data that do not depend on the official HDF5 library maintained by the HDF Group, and in particular, apart from pyfive, in Python there are none that cover the needs of environmental science. While the HDF5 c-library is reliable and performant, and battle-tested over decades, there are some caveats to depending upon it: Firstly, it is not thread-safe, secondly, the code is large and complex, and should anything happen to the financial stability of the HDF5 Group, it is not obvious the C-code could be maintained. Finally, the code complexity also meant that it is not suitable for developing bespoke code for data recovery in the case of partially corrupt data. From a long-term curation perspective both of these last two constraints are a concern.<sup>23</sup>

<sup>40</sup> The original implementation of pyfive (by JH), which included all the low-level functionality

<sup>1</sup><https://www.hdfgroup.org/solutions/hdf5/>

<sup>2</sup><https://www.unidata.ucar.edu/software/netcdf>

41 to deal with the internals of an HDF5 file was developed with POSIX access in mind. The  
42 recent upgrades were developed with the use-case of performant remote access to curated  
43 data as the primary motivation, but with additional motivations of having a lightweight HDF5  
44 reader capable of deploying in resource or operating-system constrained environments (such  
45 as mobile), and one that could be maintained long-term as a reference reader for curation  
46 purposes. The lightweight deployment consequences of a pure-Python HDF5 reader needs no  
47 further introduction, but as additional motivation we now expand on the issues around remote  
48 access and curation.

49 Thread safety has become a concern given the wide use of Dask<sup>3</sup> in Python based analysis  
50 workflows, and this, coupled with a lack of user knowledge about how to efficiently use HDF5,  
51 has led to a community perception that HDF5 is not fit for remote access (especially on cloud  
52 storage). Issues with thread safety arise from the underlying HDF5 c-library, and cannot be  
53 resolved in any solution depending on that library, hence the desire for a pure Python solution.  
54 Remote access has been bedevilled by the widespread need to access remotely data which has  
55 been chunked and compressed, combined with the use of HDF5 data which was left in the  
56 state it was when the data was produced - often with default unsuitable chunking (Rew, 2013)  
57 and with interleaved chunk indexes and data. Solutions have mainly consisted of reformatting  
58 the data (and rechunking it at the same time) or utilising kerchunk mediated direct access  
59 to chunked HDF5 data<sup>4</sup>. However, in practice using kerchunk requires the data provider to  
60 generate kerchunk indices to support remote users, and it leads to issues of synchronicity  
61 between indices and changing datasets.

62 This version of pyfive was developed with these use-cases in mind. There is now full support  
63 for lazy loading of chunked data, and methods are provided to give users all the benefits of  
64 using kerchunk, but without the need for a priori generation. Because pyfive can access and  
65 cache (in the client) the b-tree (index) on a variable-by-variable basis, most of the benefits of  
66 kerchunk are gained without any of the constraints. However, the kerchunk index is always a  
67 contiguous object accessible with one get transaction, this is not necessarily the case with the  
68 b-tree, unless the source data has been repacked to ensure contiguous metadata using a tool  
69 like h5repack. Much of the community is unaware of the possibility of repacking the index  
70 metadata, and this together with relatively opaque information about the internal structure  
71 of files (and hence the necessity or other wise of such repacking), means that repacking is  
72 rarely done. To help with this process, pyfive also includes extensions to expose information  
73 about how data and indexes are distributed in the files. With these tools, index extraction  
74 with pyfive can be comparable in performance to obtaining a kerchunk index, and completely  
75 opaque to the user.

76 With the use of pyfive, suitably repacked and rechunked HDF5 data can now be considered  
77 "cloud-optimised", insofar as with lazy loading, improved index handling, and thread-safety,  
78 there are no "format-induced" constraints on performance during remote access. To aid in  
79 discovering whether or not a given HDF5 dataset is cloud-optimised, pyfive also now provides  
80 simple methods to expose information about file layout - both in API extensions, and in a  
81 new p5dump utility packaged with the pyfive library, which provides (in the default view)  
82 functionality similar to ncldump, and when used with p5dump -s, information about storage  
83 characteristics.

84 The issues of the dependency on a complex code maintained by one private company in the  
85 context of maintaining data access (over decades, and potentially centuries), can only be  
86 mitigated by ensuring that the data format is well documented, that data writers use only the  
87 documented features, and that public code exists which can be relatively easily maintained.  
88 The HDF5group have provided good documentation for the core features of HDF5 which  
89 include all those of interest to the weather and climate community who motivated this reboot  
90 of pyfive, and while there is a community of developers beyond the HDF5 group (including

<sup>3</sup><https://www.dask.org/>

<sup>4</sup><https://fsspec.github.io/kerchunk/>

some at the publicly funded Unidata institution), recent events suggest that given most of those developers and their existing funding are US based, some spreading of risk would be desirable. To that end, a pure Python code, which is relatively small and maintained by an international constituency, alongside the existing C-code, provides some assurance that the community can maintain HDF5 access for the foreseeable future. A pure Python code also makes it easier to develop scripts which can work around data and metadata damage should they occur.

## Examples

We now introduce three aspects of the new functionality that pyfive now provides: remote access, configurable lazy loading, and determining whether files are cloud optimised.

### Remote Access

A notable feature of the recent pyfive upgrade is that it was carried out with thread-safety and remote access using fsspec (<https://filesystem-spec.readthedocs.io>) in mind. We provide two examples of using pyfive to access remote data, one in S3, and one behind a modern http web server:

For accessing the data on S3 storage, we will have to set up an s3fs virtual file system, then pass it to pyfive:

```
import pyfive
import s3fs
# storage options for an anon S3 bucket
# there are also caching options for the s3 middleware, not shown here
storage_options = {
    "anon": True,
    "client_kwargs": {"endpoint_url": "https://s3server.ac.uk"}
}
fs = s3fs.S3FileSystem(**storage_options)
file_uri = "s3-bucket/myfile.nc"
with fs.open(file_uri, "rb") as s3_file:
    nc = pyfive.File(s3_file)
    dataset = nc["var"]
```

for an HTTPS data server, the usage is similar:

```
import fsspec
import pyfive
# there are also caching options for the fsspec middleware, not shown here
fs = fsspec.filesystem("http")
with fs.open("https://site.com/myfile.nc", "rb") as http_file:
    nc = pyfive.File(http_file)
    dataset = nc["var"]
```

This is of course exactly the same pattern as remote access using h5py, and that is by design - to make moving to pyfive easy for users!

### Lazy Loading

A key tenet of efficient remote access is that variable inspection is quick and involves the minimum of network traffic between storage and the client application. However when this is coupled with the common pattern of using Dask, some flexibility in what is loaded when is beneficial.

116 By default when one inspects the contents of a file using pyfive nothing more is read from  
 117 the file than the names of the variables ("datasets" in the language of HDF5): for example:

```
118     with pyfive.File("myfile.h5", "r") as f:  
119         variables_in_file = [v for v in f]
```

118 involves nothing more than getting a set of variable names. When one wishes to inspect these  
 119 variables:

```
118     with pyfive.File("myfile.h5", "r") as f:  
119         temp = f["temp"]  
120         print(temp[1:10])
```

120 the default in pyfive is to get only the metadata associated with each variable - but crucially  
 121 at this point the b-tree index is also loaded and the variable can now be accessed outside the  
 122 context manager. Data loading is now completely lazy and the variable instance (temp) has all  
 123 the information needed to extract data as needed. This is done so that in Dask applications,  
 124 when one passes each Dask computational chunk a portion of the variable, each such Dask  
 125 chunk has already got the index, and when it does want to load data, it can be as efficient as  
 126 possible.

127 However, there are situations where loading the b-tree at variable instantiation is not wanted,  
 128 and all is wanted is to be able to view all the variable attributes. To support this option pyfive  
 129 also offers the `get_lazy_view` file method, so one can do:

```
128     with pyfive.File("myfile.h5", "r") as f:  
129         temp = f.get_lazy_view("temp")  
130         print(temp.attrs())
```

130 It is still possible to access the data and the b-tree index is loaded when data access is first  
 131 attempted.

132 This extra lazy view is new functionality. It would obviously have been possible to make the  
 133 default not load the b-tree, but in the opinion of the current pyfive maintainers loading the  
 134 b-tree at variable instantiation is likely more consistent with user expectations as it is more  
 135 equivalent to the behaviour of other packages like h5py.

## 136 Cloud Optimisation

137 To be fully cloud optimised - as defined by Stern et al. (2022) - an HDF5 file needs to have  
 138 a contiguous index for each variable, and the chunks for each variable need to be sensibly  
 139 chosen and broadly contiguous within the file. When these criteria are met, indexes can be  
 140 read efficiently, and middleware such as fsspec can make sensible use of readahead caching  
 141 strategies.

142 HDF5 data files direct from simulations and instruments are often not in this state as information  
 143 about the number of variables, the number of chunks per variable, and the compressed size of  
 144 those variables is not known as the data is being produced.

145 In such cases the data is also often not chunked along the dimensions being added to as the  
 146 file is written (since it would have to be buffered first).

147 Of course, once the file is produced, such information is available. Metadata can be repacked to  
 148 the front of the file and variables can be rechunked and made contiguous - which is effectively  
 149 the same process undertaken when HDF5 data is reformatted to other cloud optimised formats.

150 The HDF5 library provides a tool "h5repack" which can do this, provided it is driven with  
 151 suitable information about required chunk shape and the expected size of metadata fields.  
 152 pyfive supports both a method to query whether such repacking is necessary, and to extract  
 153 necessary parameters.

154 In the following example we compare and contrast the unpacked and repacked version of a  
 155 particularly pathological file, and in doing so showcase some of the pyfive API extensions  
 156 which help us understand why it is pathological, and how to address those issues for repacking.

157 If we extract just a piece of the output of p5dump -s on this file (which has surface wind  
 158 velocity at three hour intervals for one hundred years):

```

159 float64 time(time) ;
160         time:_standard_name = "time" ;
161         time:_n_chunks = 292192 ;
162         time:_chunk_shape = (1,) ;
163         time:_btree_range = (31808, 19854095942) ;
164         time:_first_chunk = 9094 ;
165
166 float32 uas(time, lat, lon) ;
167         uas:_Storage = "Chunked" ;
168         uas:_n_chunks = 292192 ;
169         uas:_chunk_shape = (1, 143, 144) ;
170         uas:_btree_range = (28672, 19854809382) ;
171         uas:_first_chunk = 36520 ;

```

172 we can immediately see that this will be a problematic file! The b-tree index is clearly interleaved  
 173 with the data (compare the first chunk address with last index addresses of the two variables),  
 174 and with a chunk dimension of (1,), any effort to use the time-dimension to locate data of  
 175 interest will involve a ludicrous number of 1 number reads (all underlying libraries read the  
 176 data one chunk at a time). It would feel like waiting for the heat death of the universe if one  
 177 was to attempt to manipulate this data stored on an object store!

178 It is relatively easy (albeit slow) to use h5repack to fix this - e.g see Hassell & Cimadevilla  
 179 Alvarez (2025) - after which we see:

```

180 float64 time(time) ;
181         time:_Storage = "Chunked" ;
182         time:_n_chunks = 1 ;
183         time:_chunk_shape = (292192,) ;
184         time:_btree_range = (11861, 11861) ;
185         time:_first_chunk = 40989128 ;
186         time:_compression = "gzip(4)" ;
187 float32 uas(time, lat, lon) ;
188         uas:_Storage = "Chunked" ;
189         uas:_n_chunks = 5844 ;
190         uas:_chunk_shape = (50, 143, 144) ;
191         uas:_btree_range = (18663, 347943) ;
192         uas:_first_chunk = 41041196 ;
193         uas:_compression = "gzip(4)" ;

```

194 Now data follows indexes, the time dimension is one chunk, and there is a more sensible  
 195 number of actual data chunks. While this file would probably benefit from splitting, with a  
 196 contiguous set of indexes, it is now possible to exploit this data via S3.

197 All the metadata shown in this dump output arises from pyfive extensions to the  
 198 pyfive.h5t.DatasetID class. pyfive also provides a simple flag: consolidated\_metadata  
 199 for a File instance, which can take values of True or False for any given file, which simplifies  
 200 at least the “is the index packed at the front of the file?” part of the optimisation question -  
 201 though inspection of chunking is a key part of the workflow necessary to determine whether or  
 202 not a file really is optimised for cloud usage.

## 203 Author contributions

204 JH designed and implemented the original software library, including all the fundamental  
205 infrastructure for working with low-level HDF artifacts. BM, WDN and BH made contributions  
206 to earlier versions of the library. BNL led the overall refresh of the library, designed and  
207 implemented the support for lazy loading of chunked data, cloud and other optimisations,  
208 and wrote the paper (with input from the other authors). EC, DH, BM, KM and VP made  
209 contributions to the recent versions of the library.

## 210 Acknowledgements

211 Most of the recent developments outlined have been supported by the UK Met Office and  
212 UKRI via 1) UK Excalibur Exascale programme (project ExcaliWork), 2) the UKRI Digital  
213 Research Infrastructure programme (project WacaSoft), and 3) the national capability funding  
214 of the UK National Center for Atmospheric Science (NCAS). Ongoing maintenance of pyfive  
215 is expected to continue under the auspices of NCAS national capability funding.

## 216 References

- 217 Folk, M., Heber, G., Koziol, Q., Pourmal, E., & Robinson, D. (2011). An overview of the HDF5  
218 technology suite and its applications. *Proceedings of the EDBT/ICDT 2011 Workshop on  
219 Array Databases*, 36–47. <https://doi.org/10.1145/1966895.1966900>
- 220 Hassell, D., & Cimadevilla Alvarez, E. (2025). *Cmip7repack: Repack CMIP7 netCDF-4  
221 datasets*. Zenodo. <https://doi.org/10.5281/zenodo.17550920>
- 222 Rew, R. (2013). Chunking data: Choosing shapes. In *News @ Unidata*. [https://www.unidata.ucar.edu/blo  
veloper/en//entry/chunking\\_data\\_choosing\\_shapes](https://www.unidata.ucar.edu/blo<br/>223 veloper/en//entry/chunking_data_choosing_shapes).
- 224 Rew, R., Hartnett, E., & Caron, J. (2006). NetCDF-4: Software implementing an enhanced  
225 data model for the geosciences. *22nd International Conference on Interactive Information  
226 Processing Systems for Meteorology, Oceanography and Hydrology*.
- 227 Stern, C., Abernathey, R., Hamman, J., Wegener, R., Lepore, C., Harkins, S., & Merose, A.  
228 (2022). Pangeo forge: Crowdsourcing analysis-ready, cloud optimized data production.  
229 *Frontiers in Climate*, 3. <https://doi.org/10.3389/fclim.2021.782909>