ECOWHEATALY

Evaluation of policies for enhancing sustainable wheat production in Italy

Work Package 1: Information gathering

Task report 1.2

LCA setup

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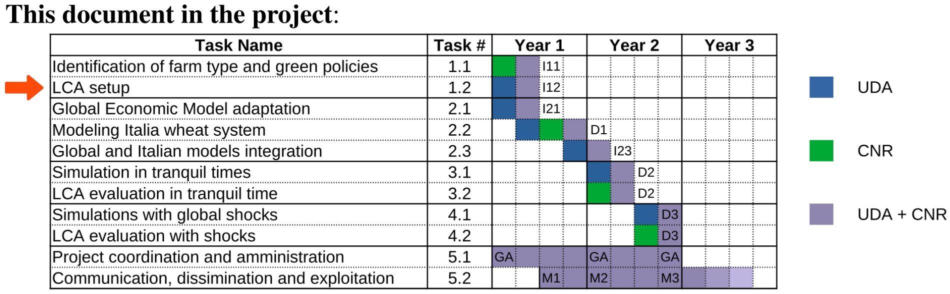

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The content of this document is the result of the worked developed by the partners in the context of the project.

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Contents

Executive Summary

This report presents the results of Task 1.2 of the ECOWHEATALY project, which focuses on the development of a Life Cycle Assessment (LCA) framework for evaluating the environmental impacts of wheat production systems in Italy. The objective of this task is to establish the methodological and computational infrastructure required to integrate environmental impact assessment into the simulation models developed within the project.

The report introduces the principles of Life Cycle Assessment according to the ISO 14040 standard and describes the main phases of the LCA procedure, including inventory analysis and impact assessment. Particular attention is devoted to the implementation of these phases using open LCA databases and the Brightway2 software framework.

The empirical basis of the analysis is provided by farm-level information derived from the RICA/FADN database, previously described in the report of Task 1.1. Using dedicated Python scripts, the variables relevant for environmental analysis are extracted from the original RICA data and organized into a structured JSON database specifically designed for the ECOWHEATALY project. This database contains detailed information on farm management practices, including machinery use, fertilizer applications, and pesticide treatments.

Based on these data, the report develops a practical implementation of LCA for wheat production systems. Production processes are constructed by linking farm-level inputs to reference processes available in existing LCA databases. Environmental impacts are then calculated using established life cycle impact assessment methods such as the IPCC climate change indicator expressed in kilograms of CO_2 equivalent.

The report also provides illustrative examples of LCA calculations for representative farms, highlighting the relative contributions of different inputs to total emissions. Preliminary results suggest that fertilizer use represents the dominant source of greenhouse gas emissions in wheat production systems, while machinery use contributes a smaller but non-negligible share.

Finally, the report introduces a matrix-based representation of the LCA model designed to support large-scale simulations within the agent-based modelling framework developed in the ECOWHEATALY project. This approach allows environmental impacts to be computed efficiently during simulations without requiring repeated database queries.

Overall, Task 1.2 establishes the environmental assessment framework that will be used in the subsequent stages of the project to analyse the environmental consequences of alternative agricultural policies and farming practices.

1 A basic introduction to LCA with open resources

According to ISO 14040 standard, LCA Analysis has to go through four phases:

- Goal and scope definition
- Inventory analysis
- Impact assessment
- Results interpretation

In this document, we focus on the *inventory analysis* and *impact assessment* phases and provide technical details. In particular, we present the mathematical foundations and a practical implementation for these two phases. The Brightway LCA software framework was chosen for the implementation because it is open source and freely available. Since Brightway LCA is written in the Python programming language, the code presented below is intended for the Python interpreter.

2 The LCA Inventory phase: LCI

2.1 Theory

This section is based on Chapter 2 of Heijungs and Suh (2002). A product system is composed of unit processes. The inputs and outputs of a unit process are collected in a vector $\mathbf{p}_i$, which contains all the items involved and their units of measurement. The vector is updated whenever a new unit process and its associated items are added.

As an example, we consider a unit process that produces 10 kWh of electricity. Figure 1 provides a graphical representation of this illustrative example.

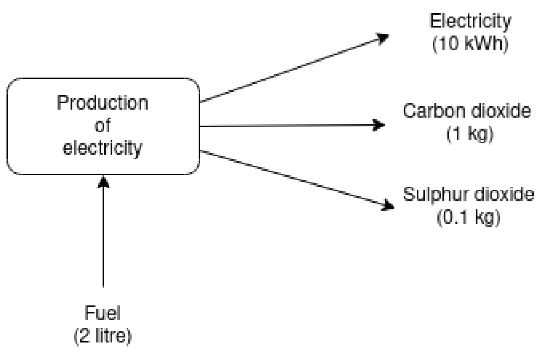

Figure 1: An illustrative example of the LCA framework.

The $\mathbf{p}_i$ collects meta data as follows:

$$\mathbf{p}_i = \begin{pmatrix} \text{litre of fuel} \\ \text{kWh of electricity} \\ \text{kg of carbon dioxide} \\ \text{kg of sulphur dioxide} \end{pmatrix}$$

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While $\mathbf{p}_1$ collects the values of $\mathbf{p}_i$, its figure becomes as follows:

$$\mathbf{p}_1 = \begin{pmatrix} -2 \\ 10 \\ 1 \\ 0.1 \end{pmatrix}$$

As a second unit process is added that accounts for the production of fuel, the scheme of Figure 1 is implemented as in Figure 2.

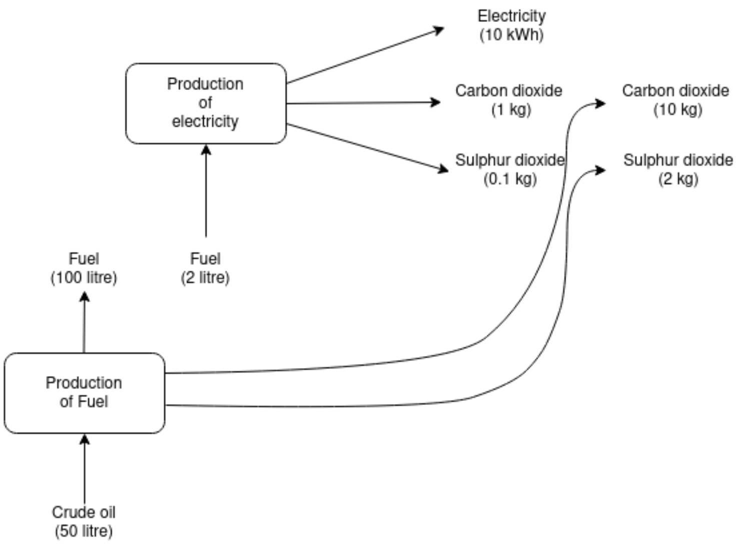

Figure 2: An illustrative example of the LCA framework: the addition of a new process.

Since we have an additional input item (crude oil), both $\mathbf{p}_i$ and $\mathbf{p}_1$ are updated as follows:

$$\mathbf{p}_i = \begin{pmatrix} \text{litre of fuel} \\ \text{kWh of electricity} \\ \text{kg of carbon dioxide} \\ \text{kg of sulphur dioxide} \\ \text{litre of crude oil} \end{pmatrix} \qquad \mathbf{p}_1 = \begin{pmatrix} -2 \\ 10 \\ 1 \\ 0.1 \\ 0 \end{pmatrix}$$

While the addition of the new process is reported in the new vector $\mathbf{p}_2$:

$$\mathbf{p}_i = \begin{pmatrix} \text{litre of fuel} \\ \text{kWh of electricity} \\ \text{kg of carbon dioxide} \\ \text{kg of sulphur dioxide} \\ \text{litre of crude oil} \end{pmatrix} \qquad \mathbf{p}_1 = \begin{pmatrix} -2 \\ 10 \\ 1 \\ 0.1 \\ 0 \end{pmatrix} \qquad \mathbf{p}_2 = \begin{pmatrix} 100 \\ 0 \\ 10 \\ 2 \\ -50 \end{pmatrix}$$

The vectors are gathered in a matrix called the *process matrix*:

$$\mathbf{P} = (\mathbf{p_1}|\mathbf{p_2}) = \begin{pmatrix} -2 & 100 \\ 10 & 0 \\ 1 & 10 \\ 0.1 & 2 \\ 0 & -50 \end{pmatrix}$$

The process matrix is partitioned into two sub-matrices:

- $\mathbf{A}$ that collects flows within the economic system, called the technology matrix;
- $\mathbf{B}$ that collects flows from the economic system into the environment and those in the reverse direction, called the intervention matrix

The intervention matrix is structured as follows:

$$\mathbf{P} = \left(\frac{\mathbf{A}}{\mathbf{B}}\right) = \left(\begin{array}{cc} -2 & 100 \\ 10 & 0 \\ \hline 1 & 10 \\ 0.1 & 2 \\ 0 & -50 \end{array}\right)$$

Let $\mathbf{f}$ denote the final demand vector. Its length is equal to the number of economic flows. Normally, it has only one non-zero entry, which is the functional unit. In our example, if we take as a functional unit 1000 kWh of electricity, we have:

$$\mathbf{f} = \begin{pmatrix} 0 \\ 1000 \end{pmatrix}$$

Furthermore, let $\mathbf{g}$ define the inventory vector, which has a length equal to the number of environmental flows as :

$$\mathbf{g} = \begin{pmatrix} g_1 \\ g_2 \\ g_3 \end{pmatrix}$$

Then, staking the final demand and the inventory vector, we obtain the aggregated external flows of the entire system:

$$\mathbf{q} = \left(\frac{\mathbf{f}}{\mathbf{g}}\right) = \left(\begin{array}{c} 0 \\ 1000 \\ \hline g_1 \\ g_2 \\ g_3 \end{array}\right)$$

Correspondingly, let $\mathbf{s}$ be the scaling vector whose length is equal to the number of economic flowsvector:

$$\mathbf{s} = \begin{pmatrix} s_1 \\ s_2 \end{pmatrix}$$

The scaling vector $\mathbf{s}$ is strictly connected to $\mathbf{f}$ troough the relation $\mathbf{As} = \mathbf{f}$. Therefore, the solution $\mathbf{s}^*$ is given by:

$$\mathbf{s}^* = \mathbf{A}^{-1}\mathbf{f}$$

The vector $\mathbf{s}^*$ indicates how many times each process must be carried out to achieve the output specified in the demand vector. In our example, we have $\mathbf{s}^* = \begin{pmatrix} 100 \\ 2 \end{pmatrix}$,

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that is the electricity production process must be implemented 100 times. Since each implementation yields 10 kWh, we obtain the requested 1,000 kWh. Furthermore, to implement the electricity production process 100 times, we need 200 litres of fuel. To obtain this amount of fuel, the fuel production process has to be implemented twice.

Accordingly, we obtain the solution of $\mathbf{g}^*$ with the following product

$$\mathbf{g}^* = \mathbf{B}\mathbf{s}^*$$

By substitution, we find a direct formulation to find $\mathbf{g}^*$ as a function of $\mathbf{f}$:

$$\mathbf{g}^* = \mathbf{B}\mathbf{A}^{-1}\mathbf{f}$$

Let us define the intensity matrix as:

$$\mathbf{\Lambda} = \mathbf{B}\mathbf{A}^{-1}$$

Consequently, the environmental flows generated by the production of $\mathbf{f}$ are obtained as:

$$\mathbf{g}^* = \mathbf{\Lambda}\mathbf{f}$$

The solution of $\mathbf{g}^*$ in our example is given by:

$$\mathbf{g}^* = \begin{pmatrix} 120 \\ 14 \\ -100 \end{pmatrix}$$

Therefore, we obtain the solution of $\mathbf{q}^*$ as follows:

$$\mathbf{q}^* = \left(\frac{\mathbf{f}}{\mathbf{g}^*}\right) = \begin{pmatrix} 0 \\ 1000 \\ \hline 120 \\ 14 \\ -100 \end{pmatrix}$$

Now, reporting $\mathbf{p}_i$ and $\mathbf{q}^*$ side by side, we have:

$$\mathbf{p}_i = \begin{pmatrix} \text{litre of fuel} \\ \text{kWh of electricity} \\ \text{kg of carbon dioxide} \\ \text{kg of sulphur dioxide} \\ \text{litre of crude oil} \end{pmatrix} \qquad \mathbf{q}^* = \begin{pmatrix} 0 \\ 1000 \\ \hline 120 \\ 14 \\ -100 \end{pmatrix}$$

We see that in the economic system, we have 1000 kWh more electricity and no additional fuel (i.e., we produced fuel, but all was used to produce electricity). In the environment, we have 120 kg more carbon dioxide, 14 kg more sulphur dioxide, and 100 litres less crude oil.

We can also calculate the output of each production process by using the columns of the $\mathbf{B}$ matrix and the elements of $\mathbf{s}^*$ as follows:

$$(\mathbf{b_1} s_1^* | \mathbf{b_2} s_2^*)$$

We can gather this information in Table 1. This is normally the output of LCI computation in LCA software.

	Electricity production	Fuel production
Carbon dioxide	100	20
Sulphur dioxide	10	4
Crude oil	0	-100

Table 1: The inventory matrix.

Before proceeding with the LCI implementation, we must distinguish between items produced and used by humans and those that already exist in nature or are produced by human activities but not used and released into the environment. The former are assigned to a set called the technosphere, while the latter are assigned to a set called the biosphere. In our example, these two sets are represented in Figure 3. We will use this terminology hereafter in the code, where we associate electricity and fuel with the technosphere, and crude oil, carbon dioxide, and sulphur dioxide with the biosphere.

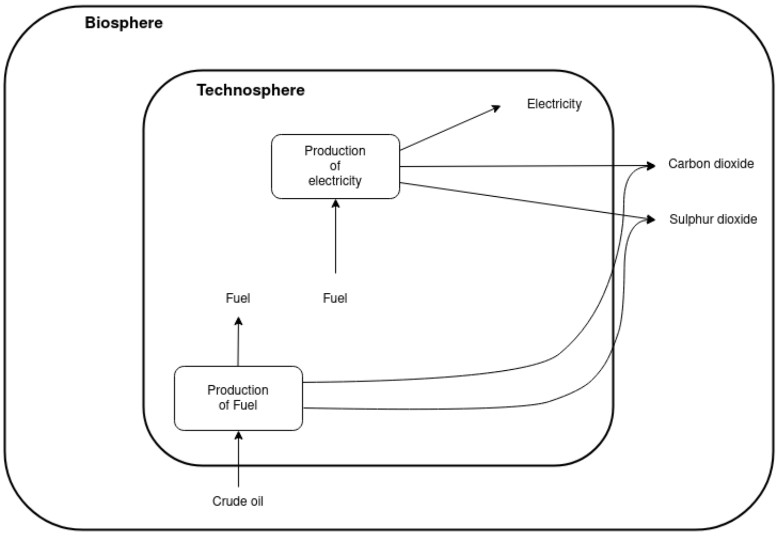


Figure 3: The connection between Technosphere and Biosphere in the LCA.

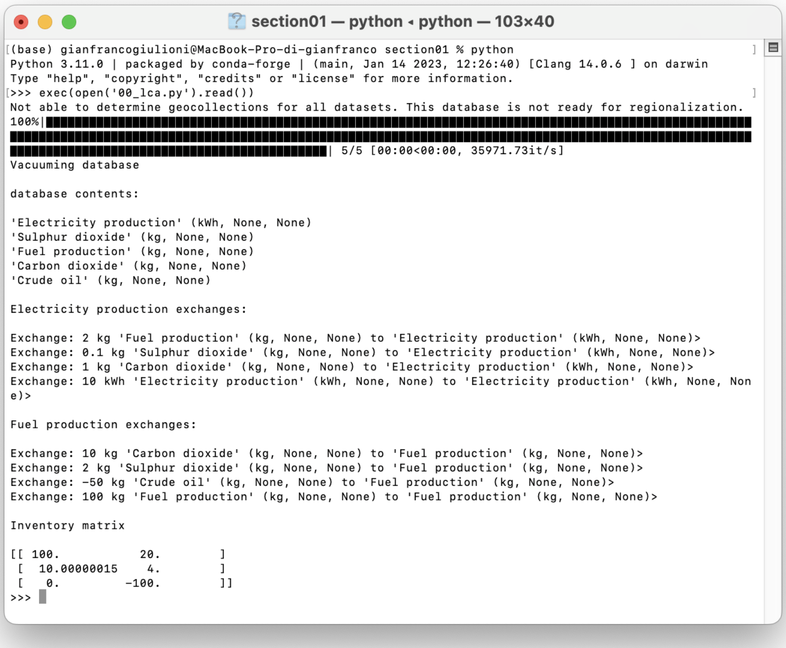
2.2 Implementation in Brightway25

The following code (also available in the `00_lca.py` script) creates a database, where the two unit processes defined above, and all the elements employed, are recorded. After some checks, the LCI is performed, and the results are displayed.

```
import bw2data as bd;
#+++++++ DATA INPUT ++++++++
t_db=bd.Database('testdb');
t_db.register();

t_db.write({
    ('testdb', 'Electricity production'):{
        'name':'Electricity production',
        'unit': 'kWh',
        'exchanges': [{
                'input': ('testdb', 'Fuel production'),
                'amount': 2,
                'unit': 'kg',
                'type': 'technosphere'
```

```
            },{
                'input': ('testdb',  'Sulphur dioxide'),
                'amount': 0.1,
                'unit': 'kg',
                'type': 'biosphere'
            },{
                'input': ('testdb',  'Carbon dioxide'),
                'amount': 1,
                'unit': 'kg',
                'type': 'biosphere'
            },{
                'input': ('testdb', 'Electricity production'), #important to write the same process name in output
                'amount': 10,
                'unit': 'kWh',
                'type': 'production'
            }]
        },
    ('testdb', 'Fuel production'):{
        'name': 'Fuel production',
        'unit': 'kg',
        'exchanges':[{
                'input': ('testdb', 'Carbon dioxide'),
                'amount': 10,
                'unit': 'kg',
                'type': 'biosphere'
            },{
                'input': ('testdb', 'Sulphur dioxide'),
                'amount': 2,
                'unit': 'kg',
                'type': 'biosphere'
            },{
                'input': ('testdb', 'Crude oil'),
                'amount': -50,
                'unit': 'kg',
                'type': 'biosphere'
            },{
                'input': ('testdb', 'Fuel production'),
                'amount': 100,
                'unit': 'kg',
                'type': 'production'
            }]
    },
    ('testdb', 'Carbon dioxide'):{'name': 'Carbon dioxide', 'unit':'kg', 'type': 'biosphere'},
    ('testdb', 'Sulphur dioxide'):{'name': 'Sulphur dioxide', 'unit':'kg', 'type': 'biosphere'},
    ('testdb', 'Crude oil'):{'name': 'Crude oil', 'unit':'kg', 'type': 'biosphere'}
    })

#++++++ SOME CHECKS +++++++++

print("");
print("database contents:");
print("");
for x in t_db.search("*"):
 print(x);

print("");
print("Electricity production exchanges:");
print("");
for x in t_db.get("Electricity production").exchanges():
 print(x);

print("");
print("Fuel production exchanges:");
print("");
for x in t_db.get("Fuel production").exchanges():
 print(x);

#++++++ PERFORM LCI +++++++++

functional_unit={t_db.get("Electricity production"): 1000};

import bw2calc as bc;
lca=bc.LCA(functional_unit);
lca.lci();

#++++++ OUTPUT TO SCREEN +++++++++

print("");
print("Inventory matrix");
print("");
print(lca.inventory.A);
```

After executing the script, the terminal should look as in Figure 4. Figures correspond to those reported in Table 1.



```
section01 — python ◂ python — 103×40
(base) gianfrancogiulioni@MacBook-Pro-di-gianfranco section01 % python
Python 3.11.0 | packaged by conda-forge | (main, Jan 14 2023, 12:26:40) [Clang 14.0.6 ] on darwin
Type "help", "copyright", "credits" or "license" for more information.
>>> exec(open('00_lca.py').read())
Not able to determine geocollections for all datasets. This database is not ready for regionalization.
100%|██████████████████████████████████████████████████| 5/5 [00:00<00:00, 35971.73it/s]
Vacuuming database

database contents:

'Electricity production' (kWh, None, None)
'Sulphur dioxide' (kg, None, None)
'Fuel production' (kg, None, None)
'Carbon dioxide' (kg, None, None)
'Crude oil' (kg, None, None)

Electricity production exchanges:

Exchange: 2 kg 'Fuel production' (kg, None, None) to 'Electricity production' (kWh, None, None)>
Exchange: 0.1 kg 'Sulphur dioxide' (kg, None, None) to 'Electricity production' (kWh, None, None)>
Exchange: 1 kg 'Carbon dioxide' (kg, None, None) to 'Electricity production' (kWh, None, None)>
Exchange: 10 kWh 'Electricity production' (kWh, None, None) to 'Electricity production' (kWh, None, Non
e)>

Fuel production exchanges:

Exchange: 10 kg 'Carbon dioxide' (kg, None, None) to 'Fuel production' (kg, None, None)>
Exchange: 2 kg 'Sulphur dioxide' (kg, None, None) to 'Fuel production' (kg, None, None)>
Exchange: -50 kg 'Crude oil' (kg, None, None) to 'Fuel production' (kg, None, None)>
Exchange: 100 kg 'Fuel production' (kg, None, None) to 'Fuel production' (kg, None, None)>

Inventory matrix

[[ 100.          20.        ]
 [  10.00000015    4.        ]
 [   0.        -100.        ]]
>>>
```

Figure 4: The output of the Python screen with the LCI procedure.

3 The LCA Impact Assessment phase: LCIA

3.1 Theory

This section is based on Chapter 8 of Heijungs and Suh (2002). Scientists have worked to identify a comprehensive list of **environmental flows**, i.e., biosphere items. The LCI phase identifies the subset of relevant flows for the specific LCA under study. In parallel, **impact categories** have also been defined.[1] These are classified as midpoint or endpoint categories (see Figure 5).

Let us choose a leading midpoint impact category to continue this tutorial: global warming. We now need to select an indicator for this impact category, such as infrared absorption. Finally, we must define a unit of measure for the indicator. Suppose we choose kilograms of CO_2-equivalent (kg CO_2-eq).

Characterization model A characterization model takes environmental flows, expressed in their respective units of measure, as input and outputs an indicator. In particular, for each environmental flow, we need to compute the effect that an additional unit has on the indicator, i.e., the partial derivative. These values are known as *characterization factors (CF)*. There is a wide variety of characterization models developed by researchers and organizations (for example, see Chapter 40 of Hauschild et al. (2018)

[1]The set of impact categories is evolving.

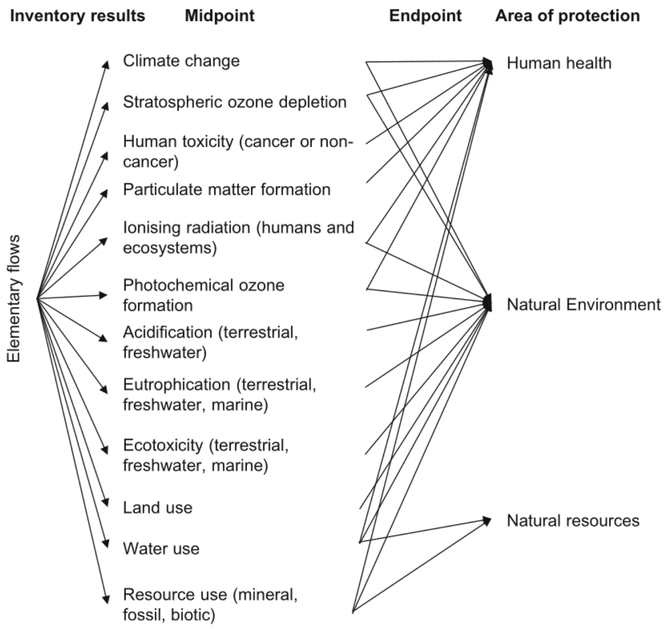


Figure 5: Relationship between LCI output and impact categories at midpoint and endpoint (source Hauschild et al. (2018) page 182).

for a comprehensive list of midpoint and endpoint methods). These models form the basis of the corresponding characterization methods.

Typically, LCA studies rely on existing characterization models. However, for practice, we will implement a simple method from scratch, following Heijungs and Suh (2002). First, we define the characterization model as shown in Table 2.

Table 2: An illustrative example of characterization model building in LCA.

impact category	Category indicator	unit of measure	CF carbon dioxide	CF sulphur dioxide	CF crude oil
global warming	infrared absorption	kg CO_2-equivalent	1	0.1	0

Secondly, we gather the CFs in a vector:

$$\mathbf{q} = \begin{pmatrix} 1 & 0.1 & 0 \end{pmatrix}$$

Finally, we compute the impact using the product $h = \mathbf{qg}$, which, in our example, results in $h = 121.4$.

3.2 Implementation in Brightway25

To describe the implementation of impact calculation in Brightway, we need to draw on the code reported in subsection 2.2, then add the following block of code:

```
#++++++++++++ METHOD DEFINITION ++++++++++

myClimateChangeCFs = [[('testdb', 'Carbon dioxide'), 1.0],
              [('testdb', 'Sulphur dioxide'), 0.1],
              [('testdb', 'Crude oil'), 0.0]];

method_key = ('simplemethodforCC', 'imaginaryendpoint', 'Climate Change');
my_CC_method = bd.Method(method_key);
my_CC_method.validate(myClimateChangeCFs);
my_CC_method.register();
my_CC_method.write(myClimateChangeCFs);
my_CC_method.load();

#++++++++ PERFORM LCA and LCIA ++++++++

lca=bc.LCA(functional_unit,method_key);
lca.lci();
lca.lcia();

#++++++ OUTPUT TO SCREEN +++++++++

print("");
print("The result of applying the method is:")
print("");
print(lca.score)
```

The upgraded code is provided in the `01_lca.py` script. The following two lines are printed on the screen in addition to the terminal output reported in Section 2.2:

```
The result of applying the method is:

121.40000003576279
```

4 Multiple LCA

4.1 Theory

In this section, we show how evaluate the impact of our biosphere items on several impact categories. In our illustrative example, the chosen impact categories are:

$$\begin{pmatrix} \text{acidification} \\ \text{global warming} \\ \text{resource depletion} \end{pmatrix}$$

For each impact category, an indicator has to be identified. Let's say they are:

$$\begin{pmatrix} H^+ \text{ release} \\ \text{infrared absorption} \\ \text{decreased availability} \end{pmatrix}$$

Finally, units of measure are chosen:

$$\begin{pmatrix} \text{kg } SO_2\text{−equivalent} \\ \text{kg } CO_2\text{−equivalent} \\ \text{resource depletion units (RDU)} \end{pmatrix}$$

Characterization models For each indicator expressed in a given unit of measure, we build a characterization model, i.e., a set of CF. Again, we proceed from scratch rather than relying on several existing characterization models to gain some more practice.

If we index the indicators (each linked to one of the various impact categories) with i, the environmental flow with j, and denote the CFs with q_{ij}, each row of the Table 3 represents a characterization model.

Table 3: Definition of multiple indicators, each associated with an impact category in LCA.

	ef_1	$\cdots$	ef_n
ic_1	$q_{1,1}$	$\cdots$	$q_{1,J}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
ic_I	$q_{I,1}$	$\cdots$	$q_{I,n}$

where ic_i denotes impact categories, and ef_j is environmental flows.

In our example, among the lines of the previous table we have to extract those corresponding to kg SO_2-equivalent kg CO_2-equivalent and RDU. Suppose this extraction leads us to:

	kg carbon dioxide	kg sulphur dioxide	litre crude oil
kg SO_2-equivalent	0	1	0
kg CO_2-equivalent	1	0.1	0
RDU	0	0	-15

It is straightforward to build the corresponding matrix

$$\mathbf{Q} = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0.1 & 0 \\ 0 & 0 & -15 \end{pmatrix}$$

The environmental impacts we are interested in are computed as follows

$$\mathbf{h} = \mathbf{Qg}$$

where $\mathbf{g}$ is the outcome of the inventory phase (see the previous section). In our example, we have

$$\mathbf{h} = \begin{pmatrix} 14 \\ 121.4 \\ 1500 \end{pmatrix}$$

4.2 Implementation in Brightway25

In the Brightway code, we must define two additional characterization models: one for acidification and one for resource depletion. Afterward, we can run the code from the previous script three times, changing the assessment method at each iteration. Alternatively, we can use Brightway's `MultiLCA` class, which performs LCA on a list of functional units and/or a list of different methods. We proceed using the `MultiLCA` class with one functional unit (the same as before) and the three defined characterization models. The Python script remains the same up to the method definition; the rest should be replaced by the following:

```
#++++++++++++ METHODS DEFINITION ++++++++++

myClimateChangeCFs = [[('testdb', 'Carbon dioxide'), 1.0],
               [('testdb', 'Sulphur dioxide'), 0.1],
               [('testdb', 'Crude oil'), 0.0]];
```

```
cc_method_key = ('simplemethodforCC', 'imaginaryendpoint', 'Climate Change');
my_CC_method = bd.Method(cc_method_key);
my_CC_method.validate(myClimateChangeCFs);
my_CC_method.register();
my_CC_method.write(myClimateChangeCFs);
my_CC_method.load();



myAcidificationCFs = [[('testdb', 'Carbon dioxide'), 0.0],
              [('testdb', 'Sulphur dioxide'), 1.0],
              [('testdb', 'Crude oil'), 0.0]];

ac_method_key = ('simplemethodforAC', 'imaginaryendpoint', 'Acidification');
my_AC_method = bd.Method(ac_method_key);
my_AC_method.validate(myAcidificationCFs);
my_AC_method.register();
my_AC_method.write(myAcidificationCFs);
my_AC_method.load();



myResourceDepletionCFs = [[('testdb', 'Carbon dioxide'), 0.0],
              [('testdb', 'Sulphur dioxide'), 0.0],
              [('testdb', 'Crude oil'), -15.0]];

rd_method_key = ('simplemethodforRD', 'imaginaryendpoint', 'Resource depletion');
my_RD_method = bd.Method(rd_method_key);
my_RD_method.validate(myResourceDepletionCFs);
my_RD_method.register();
my_RD_method.write(myResourceDepletionCFs);
my_RD_method.load();

#++++++++ PERFORM MULTIPLE LCA ++++++++

functional_unit={t_db.get("Electricity production"): 1000};
functional_units=[functional_unit];
chosen_methods=[cc_method_key,ac_method_key,rd_method_key];
my_calculation_setup = {'inv': functional_units, 'ia': chosen_methods};

bd.calculation_setups['set of calculation setups'] = my_calculation_setup;
mlca = bc.MultiLCA('set of calculation setups');

#++++++ OUTPUT TO SCREEN +++++++++

print("");
print("The results of applying the methods are:")
print("");
print(mlca.results)
```

The upgraded code is provided in the `02_lca.py` script. The following two lines are printed on the screen in addition to the terminal output reported in Section 2.2:

```
The results of applying the methods are:
                                                        score   unit
simplemethodforCC imaginaryendpoint Climate Change       121.4  cc-eq
simplemethodforAC imaginaryendpoint Acidification         14.0  ac-eq
simplemethodforRD imaginaryendpoint Resource depletion  1500.0  rd-eq
```

5 Brightway database and impact methods

In the previous sections, we created our own database and defined our own assessment methods. However, most practitioners performing an LCA focus on technosphere modeling and typically take the biosphere flows and impact assessment methods as given.

In practice, biosphere flows and impact assessment methods change slowly over time. The biosphere flows reflect available natural resources and known chemical elements, while impact assessment methods are developed by researchers and require time to be tested and refined.

In general, LCA software is distributed with a predefined biosphere database and a set of available impact assessment methods. These two components are closely linked because the methods take biosphere flows as inputs. Consequently, the variable names used in the impact assessment methods must match the corresponding names used in the biosphere database.

Like other LCA software, Brightway includes a biosphere database and a set of currently available impact assessment methods. To make them usable, we first need to configure Brightway with the following code:

```
import bw2io as bi
bi.bw2setup()
```

After the execution, we can check the status of our environment with the following commands:

```
import bw2data as bd
bd.databases
bd.methods
```

In the database list, we now have the `biosphere3` database, and many assessment methods are listed with the `bd.methods` command.

5.1 Exploring the biosphere database

To explore the content of `biosphere3`, we can run the commands:

```
bs3=bd.Database('biosphere3')
list(bs3)
```

or use for loops for a more readable output, such as

```
for activity in bs3:
 print(activity);
```

and

```
for activity in bs3:
 print(activity.get('type'),"    ",activity.get('name'))
```

Let us suppose we are interested in coal, so we search for coal as follows:

```
coal_items=bs3.search(``coal'')
```

then, examine the three activities output by the software:

```
'Coal, brown' (kilogram, None, ('natural resource', 'in ground'))
'Coal, hard, unspecified' (kilogram, None, ('natural resource', 'in ground'))
'Gas, mine, off-gas, process, coal mining' (standard cubic meter, None, ('natural resource', 'in ground'))
```

Furthermore, if we are interested in having additional information on the second item, for example, it can be done by typing the following command:

```
coal_items[1].as_dict()
```

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5.2 Exploring assessment methods

To explore the assessment methods, type `bd.methods` to print a few of them, `list(bd.methods)` for all of them, or, for a more readable output, the following for loop:

```
for method in bd.methods:
 print(method)
```

Searching for a specific set of methods can be done by storing them in a list:[2]

```
IPCC2013_methods = [m for m in bd.methods if 'IPCC 2013' in str(m)]
for method in IPCC2013_methods:
 print(method)
```

By adding `and` conditions, it is also possible to refine the search:

```
CC_method = [m for m in bd.methods if 'IPCC 2013' in str(m) and
    'climate change' in str(m) and
    'GWP 100a' in str(m) and
    not 'no LT' in str(m)][0]
CC_method
```

As explained above, the core of an assessment method is represented by characterization factors (CFs). To view CFs, we can use the `load()` function. For example, the following code prints out the CFs of the fourth assessment method in the methods list:

```
method_n=3
print("method info: "+str(list(bd.methods)[method_n]))

method_cfs=bd.Method(list(bd.methods)[method_n]).load()
for cf in method_cfs:
    print(cf)
```

The output produced by executing the above command appears rather puzzling, although it is quite informative.

```
(['biosphere3', '9990b51b-7023-4700-bca0-1a32ef921f74'], 1.6)
(['biosphere3', '8c52f40c-69b7-4538-8923-b371523c71f5'], 1.2)
(['biosphere3', '7ecc2b66-8dde-4266-8832-f492f564377b'], 0.783673469)
(['biosphere3', '0f440cc0-0f74-446d-99d6-8ff0e97a2444'], 1.6)
.. .. ..
```

In particular, the second figure in each line indicates that each biosphere item is represented by a code. Thanks to this code, we can use the one-to-one correspondence between variables in the biosphere database and the assessment methods mentioned above to obtain a human-readable output of the CFs. In fact, the biosphere database holds both human-readable descriptions of flows and their corresponding codes. The following for loop retrieves the name of each biosphere flow from the biosphere database using the code obtained from the assessment methods:

```
for cf in method_cfs:
    print(str(bs3.get(cf[0][1]))+" .......... CF: "+str(cf[1]))
```

which delivers this output:

```
'Ammonia' (kilogram, None, ('air', 'urban air close to ground')) .......... CF: 1.6
'Sulfur dioxide' (kilogram, None, ('air', 'urban air close to ground')) .......... CF: 1.2
'Sulfuric acid' (kilogram, None, ('air', 'urban air close to ground')) .......... CF: 0.783673469
'Ammonia' (kilogram, None, ('air', 'non-urban air or from high stacks')) .......... CF: 1.6
.. .. ..
```

[2] Some methods have no LT variant to take into account the Long Term (LT) effect of emissions or not. This is because the Econinvent database has such a distinction. However, in some cases, this distinction is not available. See https://support.ecoinvent.org/lcia-results for a discussion.

6 Third-party LCI databases

In the previous sections, we noted that the typical application of LCA is in the modeling of the technosphere. Let us now suppose that we want to assess the environmental impact of wheat production using data collected from a specific farm. By organizing and analyzing the available data, we can state, for example, that each hectare devoted to wheat cultivation:

- produces 3 tons of wheat
- produces 1 ton of straw
- requires 100kg of fuel for tractors
- requires 50kg of fertilizer
- requires 2 liters of pesticides

This is what economists call the wheat production function.

However, behind this production function, there are many other, more detailed production functions. For example, tractor operation is one of them: it takes fuel as input and produces useful energy as output, along with various pollutants emitted from the exhaust pipe.

Other relevant production functions include fuel production, the production of fertilizers and pesticides, and the application of those fertilizers and pesticides.

Developing all these production functions from scratch is a demanding task because it requires expertise in several different fields. Therefore, it is natural to investigate whether others have already completed at least part of this work.

A number of LCI databases have been created, each compiling a large set of such production functions. As a result, LCA studies are often carried out using third?party LCI databases, even though these databases are frequently proprietary and use their own data formats.[3]

6.1 Free resources for LCA

An effort to enable free LCA analysis is provided by the *openLCA project* (openlca.org), which maintains the openLCA software and makes it freely available. openLCA also provides an API for programmatic interaction (details are available at the bottom of this web page).

Moreover, the openLCA Nexus initiative (nexus.openlca.org) offers free downloads of several databases.[4] The databases in the openLCA Nexus download section typically use the openLCA data format (called *zolca*).

The U.S. Department of Agriculture (USDA) LCA Commons database is among those freely available in the openLCA Nexus download section. A closer examination of the databases shows that it contains several datasets potentially useful for the ECOWHEATALY project. We therefore describe below the contents of one such dataset. In this database, we find, for example, the process `winter wheat produ ction; conventional tillage; US average; at regional sto`

[3]The task of performing a fully open LCA is further complicated by the fact that LCA software packages also use different data management approaches. For example, Brightway uses SQLite to manage data, so external databases must first be converted into the appropriate SQLite format.

[4]Free registration on the website is required to access the download section.

rage; 14\% MC. It can be found under: University of Arkansas → Agriculture, forestry and fishing → Growing of cereals.

We examined this process using openLCA. In particular, we transformed it into a product system and obtained a visual representation by clicking the Model graph tab (see Figure 6). We present this process here because it has a compact visual representation. Furthermore, the basic example discussed in the next section uses a different process from the same database, which serves as an input for wheat production.

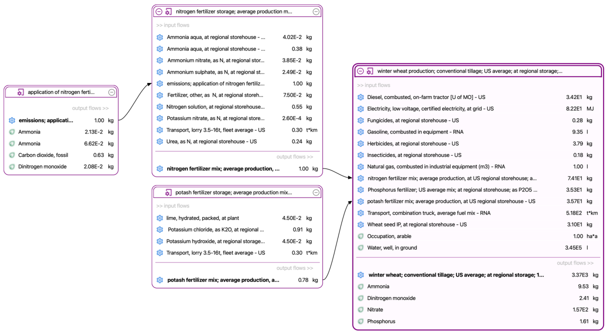


Figure 6: A visual representation of LCA process winter wheat production; conventional tillage; US average; at regional storage; 14 \% MC in USDA LCA Commons.

6.2 Using Brightway with free resources

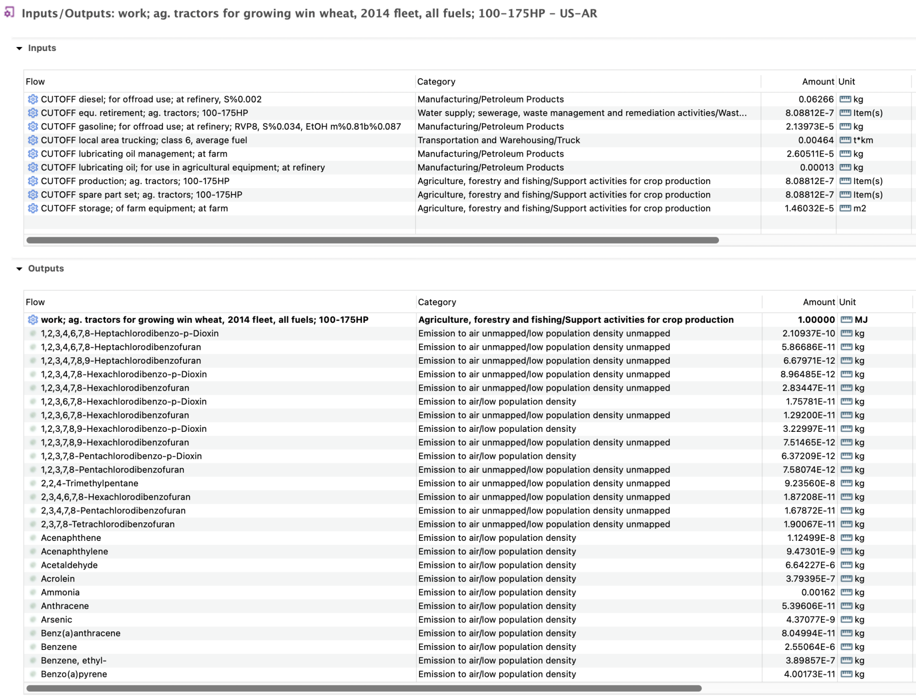
In this section, we model a simplified wheat production process to show how to import and use an external resource in the Brightway software. Suppose we want to perform an LCA of a farm producing winter wheat in Arizona. After modeling the technosphere, we find that the farm uses only 1 megajoule of tractor work per acre.

Browsing the available databases, we see that USDA?s LCA Commons includes the ?University of Washington Design for Environment Laboratory/Field Crop Production? database, which contains several processes describing agricultural tractor work for different crops in various U.S. states. Among these, there is a process named work; ag. tractors for growing win wheat, 2014 fleet, all fuels; 100?175 HP - US-AR, which provides the inputs and outputs for an agricultural tractor delivering 1 megajoule of work in winter wheat production in Arizona. In Figure 7, the screenshot of the input-output tab in OpenLCA shows an insight into the mentioned process.

We now export the process from OpenLCA in *EcoSpold* process format in a folder (say EcoSplod01), such that the directory contains the process_c0508675-d384-7e78-c6cd-e9c951ec8396.xml file (this is *EcoSpold1* format).

The code to import the *EcoSplod1 class* into Brightway is as follows:

```
import bw2io as bi
```


Inputs/Outputs: work; ag. tractors for growing win wheat, 2014 fleet, all fuels; 100-175HP - US-AR

Inputs

Flow	Category	Amount	Unit
CUTOFF diesel; for offroad use; at refinery, S%0.002	Manufacturing/Petroleum Products	0.06266	kg
CUTOFF equ. retirement; ag. tractors; 100-175HP	Water supply; sewerage, waste management and remediation activities/Wast...	8.08812E-7	Item(s)
CUTOFF gasoline; for offroad use; at refinery; RVP8, S%0.034, EtOH m%0.81b%0.087	Manufacturing/Petroleum Products	2.13973E-5	kg
CUTOFF local area trucking; class 6, average fuel	Transportation and Warehousing/Truck	0.00464	t*km
CUTOFF lubricating oil management; at farm	Manufacturing/Petroleum Products	2.60511E-5	kg
CUTOFF lubricating oil; for use in agricultural equipment; at refinery	Manufacturing/Petroleum Products	0.00013	kg
CUTOFF production; ag. tractors; 100-175HP	Agriculture, forestry and fishing/Support activities for crop production	8.08812E-7	Item(s)
CUTOFF spare part set; ag. tractors; 100-175HP	Agriculture, forestry and fishing/Support activities for crop production	8.08812E-7	Item(s)
CUTOFF storage; of farm equipment; at farm	Agriculture, forestry and fishing/Support activities for crop production	1.46032E-5	m2

Outputs

Flow	Category	Amount	Unit
work; ag. tractors for growing win wheat, 2014 fleet, all fuels; 100-175HP	**Agriculture, forestry and fishing/Support activities for crop production**	**1.00000**	**MJ**
1,2,3,4,6,7,8-Heptachlorodibenzo-p-Dioxin	Emission to air unmapped/low population density unmapped	2.10937E-10	kg
1,2,3,4,6,7,8-Heptachlorodibenzofuran	Emission to air unmapped/low population density unmapped	5.86686E-11	kg
1,2,3,4,7,8,9-Heptachlorodibenzofuran	Emission to air unmapped/low population density unmapped	6.67971E-12	kg
1,2,3,4,7,8-Hexachlorodibenzo-p-Dioxin	Emission to air unmapped/low population density unmapped	8.96485E-12	kg
1,2,3,4,7,8-Hexachlorodibenzofuran	Emission to air unmapped/low population density unmapped	2.83447E-11	kg
1,2,3,6,7,8-Hexachlorodibenzo-p-Dioxin	Emission to air/low population density	1.75781E-11	kg
1,2,3,6,7,8-Hexachlorodibenzofuran	Emission to air unmapped/low population density unmapped	1.29200E-11	kg
1,2,3,7,8,9-Hexachlorodibenzo-p-Dioxin	Emission to air/low population density	3.22997E-11	kg
1,2,3,7,8,9-Hexachlorodibenzofuran	Emission to air unmapped/low population density unmapped	7.51465E-12	kg
1,2,3,7,8-Pentachlorodibenzo-p-Dioxin	Emission to air/low population density	6.37209E-12	kg
1,2,3,7,8-Pentachlorodibenzofuran	Emission to air unmapped/low population density unmapped	7.58074E-12	kg
2,2,4-Trimethylpentane	Emission to air unmapped/low population density unmapped	9.23560E-8	kg
2,3,4,6,7,8-Hexachlorodibenzofuran	Emission to air unmapped/low population density unmapped	1.87208E-11	kg
2,3,4,7,8-Pentachlorodibenzofuran	Emission to air unmapped/low population density unmapped	1.67872E-11	kg
2,3,7,8-Tetrachlorodibenzofuran	Emission to air unmapped/low population density unmapped	1.90067E-11	kg
Acenaphthene	Emission to air/low population density	1.12499E-8	kg
Acenaphthylene	Emission to air/low population density	9.47301E-9	kg
Acetaldehyde	Emission to air/low population density	6.64227E-6	kg
Acrolein	Emission to air/low population density	3.79395E-7	kg
Ammonia	Emission to air/low population density	0.00162	kg
Anthracene	Emission to air/low population density	5.39606E-11	kg
Arsenic	Emission to air/low population density	4.37077E-9	kg
Benz(a)anthracene	Emission to air/low population density	8.04994E-11	kg
Benzene	Emission to air/low population density	2.55064E-6	kg
Benzene, ethyl-	Emission to air/low population density	3.89857E-7	kg
Benzo(a)pyrene	Emission to air/low population density	4.00173E-11	kg

Figure 7: A visual representation of LCA process `work; ag. tractors for growing win wheat, 2014 fleet, all fuels; 100?175 HP - US-AR` in University of Washington Design for Environment Laboratory/Field Crop Production? database belonging to USDA LCA Commons.

```
#importing a process exported from openLCA software
ei_path="EcoSpold01"
ei_name="usda_item"
ei_importer = bi.SingleOutputEcospold1Importer(ei_path, ei_name)
```

Now, checking with `ei_importer.statistics()`, we see that many flows are unlinked. This means that the imported variables are not present in the `biosphere3` database.

6.2.1 Managing a single process

Brightway includes a mechanism to attempt linking unlinked flows. However, it works reliably only for well-established databases such as *Ecoinvent*.

When working with a single process, the most straightforward approach is to create a new process, replacing the flows of the original process with the most similar ones found in the Brightway `biosphere3` database. For each item in the original process, we can, for example, find the best match in the `biosphere3` database using the *matching sentence* Python package.

We can then follow the instructions in Section 2.2 to build the new process. During this step, each input should be assigned the name and code from the corresponding `biosphere3` flow, while retaining the quantities from the original dataset. This procedure is implemented in the script `03_lca.py`.

Because the new process is fully compliant with `biosphere3`, there is a complete correspondence with the Brightway implementation of impact assessment methods. All Brightway methods can therefore be used, thanks to the one-to-one correspondence between the variables used by the methods and the flows in the `biosphere3` database. In particular, as reported in Section 5.2, the matching can be performed by codes (i.e., identifiers such as `9990b51b-7023-4700-bca0-1a32ef921f74`). In this way, process items and characterization factors (CFs) can be matched exactly.

Script `03_lca.py` provides first some warnings on the replacements, when the matching score is acceptable. It further informs on the CFs discarded because of a poor matching score. Finally, it performs the Life Cycle Assessment using the `'IPCC 2013', 'climate change', 'global warming potential (GWP100)` method, taking as a functional unit the same as the process output (1 megajoule of tractor power).

Here are the results:

```
Applied Brightway2 Method:
  IPCC 2013: climate change: global warming potential (GWP100)
  that delivered
  0.20238206659649227 kg CO2-Eq

Processes contribution:

(0.20238206659649227, 1.0,
  'work; ag. tractors for growing win wheat, 2014 fleet, all fuels; 100-175HP' (MJ, None, None))

EMISSION CONTRIBUTION  ################################

(0.19874133169651031, 0.19874133169651031,
  'Carbon dioxide, fossil' (kilogram, None, ('air', 'low population density, long-term')))

(0.002253353985787465, 0.0005546854226849973,
   'Carbon monoxide, fossil' (kilogram, None, ('air', 'low population density, long-term')))

(0.0013305875634225528, 5.024877737014322e-06,
   'Dinitrogen monoxide' (kilogram, None, ('air', 'low population density, long-term')))

(5.6793350771930026e-05, 1.9122339836030733e-06,
  'Methane, fossil' (kilogram, None, ('air', 'low population density, long-term')))
```

A more straightforward approach is to download the process in JSON-LD format from the LCA Commons website. This format includes the codes that can be matched directly to those in `biosphere3`. The `02_lca_json_ld.py` script imports the JSON-LD file, creates the process in Brightway, and performs the same LCA as above, yielding identical results.

6.2.2 An alternative way: importing process and method with method adaptation

There is an alternative way to achieve the same result presented in Section 6.2.1. It consists of importing both the data and the methods, establishing a one-to-one correspondence. However, for several impact categories, we must import all assessment methods of interest. We also present this alternative approach because it helps to clarify how the biosphere?method interaction works.

We now reconstruct part of the Brightway EcoSpold1 import class as follows:

```
import bw2io as bi

# importing a process exported from openLCA software

ei_path = "EcoSpold01"

ei_name = "usda_item"
```

```
ei_importer = bi.SingleOutputEcospold1Importer(ei_path, ei_name)
```

By checking `ei_importer.statistics()`, we see that many flows are unlinked. Brightway includes a mechanism to attempt to link unlinked flows, implemented by the following line of code:

```
ei_importer.apply_strategies()
```

However, checking `ei_importer.statistics()` again, we verify that we had little success. To address the issue of unlinked flows, we can add the unlinked imported variables to the `biosphere3` database with the command:

```
ei_importer.add_unlinked_flows_to_biosphere_database()
```

Nevertheless, this operation alone does not yet enable LCA analysis, because the Brightway methods are not aware of the newly added variables in `biosphere3`.[5] We will return to this issue after completing the import process, which adds the `ei_name` database with the new technosphere items to the set of available databases.

```
ei_importer.add_unlinked_activities()
ei_importer.write_database()
```

Back to the issue presented above: Brightway?s treatment of impact assessment methods ignores the new biosphere variables. For example, attempting to perform an impact assessment using the Brightway *IPCC GWP 100a* method[6] returns an output of 0 kg CO_2-equivalent. However, performing the same analysis with openLCA yields approximately 0.2 kg CO_2-equivalent.

To address this discrepancy, we import the relevant impact assessment method from openLCA. In openLCA, the *Indicators and parameters* section lists, among other elements, the available impact assessment methods. From openLCA, we export the desired impact assessment method in EcoSpold format to a folder (e.g. `EcoSpold01\_lcia`). An XML file corresponding to the method will be contained in that folder.

As mentioned above, we use the *IPCC GWP 100a* method, which evaluates climate change in kg CO_2-equivalent. We import this method using the following code:

```
#importing a method exported from openLCA software

method_path = "EcoSpold01_lcia"

method = bi.Ecospold1LCIAImporter(method_path)
```

Finally, we create a new method that includes the new variables and add it to the `biosphere3` database. The code used is the following:

[5] The LCIA formatter tool is a possible solution to this issue (LCIA formatter).
[6] This method is part of the IPCC 2013 set.

```
#Porting the imported method in brightway
original_name=list(method)[1]['name']
new_name=(original_name[0],original_name[1],str(original_name[2])+' from OpenLCA')
original_exchanges=list(method)[1]['exchanges']
bs3=bd.Database('biosphere3')
#creating CFs
CFs_list=[]
for oe in original_exchanges:
    for bsi in bs3:
        if (oe['name']==bsi['name']) and (str(oe['categories'])==str(bsi['categories'])):
            CFs_list.append([bsi.key,oe['amount']])

my_CC_method = bd.Method(new_name)
my_CC_method.validate(CFs_list)
my_CC_method.register()
my_CC_method.write(CFs_list)
my_CC_method.load();
```

We now perform the LCA analysis, setting the functional unit to 1 megajoule of tractor work. The result is 0.20012743273605338 kg CO2-equivalent. Exactly as in OpenLCA.

```
#computing lca for the imported process
import bw2calc as bc
usdadb=bd.Database('usda_item')
functional_unit={usdadb.get('ccfa048cb86343798ac04f50a504c3af'):1}
method_key=new_name
lca=bc.LCA(functional_unit,method_key)
lca.lci()
lca.lcia()
print(lca.score)
```

The `03_lca_2.py` script loads the EcoSpold1 process and adds new variables to the `biosphere3` database. The `03_lca_2_lcia.py` script loads the method and, based on this, creates a new method providing CFs to the new variables.

6.2.3 Importing a process from a CSV file

As another exercise, we implement the method described in Section 6.2.1 on a process provided in a CSV file. Sometimes, process data can be taken directly from tables reported in the literature. In these cases, it is convenient to arrange the information in a CSV file. The `04_lca.py` script is designed to load such CSV files. It also synchronizes the variables with the `biosphere3` database and performs the usual LCA.

6.3 Other databases

There are many life cycle inventory (LCI) databases available. For example, *Ecoinvent* is one of the world?s leading LCI databases. It includes both commercial and freely accessible datasets. Of particular interest for the ECOWHEATALY project are the agri-food databases:

- Agri-footprint. It has both commercial and free components.
- AGRIBALYSE is a French LCI database for the agriculture and food sector. It is distributed via the OpenLCA and SimaPro software. A licence purchase is required, except for French researchers and small enterprises.
- World Food LCA Database (WFLDB).
- Swiss Agricultural Life Cycle Assessment (SALCA).

- LCA Food (lcafood.dk) is a free database. The data can be accessed through the commercial LCA software SimaPro (nx1 extension). However, an attempt to open the database using the latest SimaPro trial version shows that processes are not loaded correctly, probably due to version incompatibility, as the LCA Food database was released in 2006.

6.4 Further reading and information

The following two books can be used to gather more info:

1. Su (2020)
   (a) Chapter 3: Review of LCIA methods
   (b) Chapter 4: LCA software
   (c) Chapter 12: Assessment of farming (use Ecoinvent p. 254 LCIA: ReCiPe because it has both midpoint and endpoint; sortware: SimaPro)
2. Hauschild et al. (2018)
   (a) Chapter 9 page 117: LCI
   (b) Chapter 10 page 167: LCIA
   (c) Chapter 40 page 1147: Overview of existing LCIA method - annex to Chapter 10
   (d) Chapter 29: LCA of food and agriculture. Page 741 par 29.3.2.1 Crop Production. Use of Swiss Agriculture Life Cycle Assessment (SALCA)

We report hereafter useful acronyms:

- ISO is the International Organization for Standardization acronym.
- EN identifies regulation from CEN (Comité Européen de Normalisation).
- UNI is the acronym of "Ente nazionale italiano di unificazione". It represents Italy at the European (CEN) and World (ISO) levels.

7 LCA implementation for Ecowheataly farms

7.1 Descriptive statistics of farm management for Italian durum wheat cropping system

Information on the management of farms producing durum wheat in Italy is retrieved from the RICA database, which is fully described in the Report of Task 1.1.

Starting from RICA Excel files produced through specific scripts developed within the framework of ECOWHEATALY, we built a database containing the variables relevant for LCA. This database consolidates into a single JSON-formatted source the variables originally dispersed across multiple Excel files. An overview of the ECOWHEATALY JSON database is also provided in the Report of Task 1.1.

Because RICA is a proprietary database, we cannot distribute it. Nevertheless, we provide the `01_create_json_database_for_lca.py` Python script, which takes the Excel files as input and generates the `ecowheataly_database_lca.json` file.

Furthermore, the `ecowheataly_lca_database_stats.py` script loads the ECOWHEATALY JSON database and produces the preliminary statistics reported in the following tables.

The database includes data from 14,168 farms. Since RICA is a sampling database, where farms are replaced every n years, each farm contributes data for one or more years between 2008 and 2021. Table 4 reports the frequency distribution of the number of years each farm supplied data to RICA.

Table 4: Duration of farms data contribution to RICA database before replacement.

farm age	farms count
1	4431
2	3036
3	1773
4	1368
5	957
6	764
7	423
8	358
9	230
10	229
11	150
12	172
13	106
14	171

Table 5 reports the number of participating farms in each year and the hectares they cultivated. The table shows, for example, that farms tend to specialize in either durum or soft wheat, with relatively few farms growing both types. Durum wheat is the most widely cultivated in Italy, although the gap between durum and soft wheat narrows over time.

Table 6 reports a count of farms using fertilizers and pesticides. Fertilizers and herbicides are largely used. A moderate number of farms use insecticides, while a few use adjuvants.

To appropriately investigate input use, we examine how the sample size changes as we impose increasingly strict specialization requirements. First, we set a minimum threshold of 2 hectares for wheat cultivation. Then, we calculate the share of each farm's land devoted to wheat. The following tables report the number of farms whose percentage of land dedicated to wheat exceeds the thresholds indicated in the column headings.

Table 5: Number of farms and corresponding acreage dedicated to durum and soft wheat cropping in RICA.

years	n durum only	n soft only	n both	n farms total	ha durum	ha soft	ha total
2008	1822	1596	281	3699	40945	19716	60661
2009	1646	1405	226	3277	36090	17013	53103
2010	1803	1447	250	3500	36761	17513	54274
2011	1745	1344	199	3288	32783	15322	48105
2012	1878	1548	219	3645	36233	19620	55853
2013	1684	1607	206	3497	31725	19852	51578
2014	1587	1487	193	3267	29388	17214	46602
2015	1595	1346	232	3173	28768	15726	44494
2016	1855	1320	320	3495	33910	17369	51279
2017	1761	1379	280	3420	31594	17178	48771
2018	1716	1519	335	3570	30221	20152	50373
2019	1616	1487	312	3415	29104	19046	48151
2020	1646	1455	326	3427	29332	19463	48795
2021	1701	1607	353	3661	30871	21570	52441

7.2 Machinery use

Among the freely available datasets for machinery use in agriculture, the USDA's LCA Commons provides the "University of Washington Design for Environment Laboratory/Field Crop Production" database, which includes several processes related to the operation of agricultural tractors for various crops in several US states.

For a first implementation, we randomly selected one of these processes. The process is named `work; ag. tractors for growing win wheat, 2014 fleet, all fuels; 100-175HP - US-AR` and describes the inputs and outputs of an agricultural tractor delivering 1 megajoule of work in winter wheat production in Arizona. To provide further insight, the screenshot shown in Figure 8 is taken from the input-output tab in OpenLCA for the selected process.

We load the process into Brightway as explained in Section 4.2. The source code used for the import is provided in the `03_lca_import_tractor_use_process.py` script, while the source code to perform LCA is in `lca_machinery.py`.

Among the available impact assessment methods, we chose IPCC GWP 100a, which evaluates climate change (GWP: Global Warming Potential) in terms of kilograms of CO_2-equivalent. Before performing the LCA, we must link our data to this process. Specifically, our data are expressed in hours of machinery use, whereas the process unit is Megajoules.

To this end, we use the conversion 1 $Megajoule = 0.2778\ Chilowattora(Kw)$ such that a 100 Kw tractor used for 1 hour produces $100/0.2778 = 360$ megajoules.

Now, suppose we want to perform an LCA for a farm that uses a tractor for 2.5 hours/ha, corresponding to 900 megajoules. We need to implement the process for

Table 6: Number of farms using fertilizers and pesticides for durum and soft wheat cropping in RICA.

years	n farms durum using fertilizers	n farms durum using herbicides	n farms durum using insecticides	n farms durum using coadjuvants	n farms soft using fertilizers	n farms soft using herbicides	n farms soft using insecticides	n farms soft using coadjuvants	n farms both using fertilizers	n farms both using herbicides	n farms both using insecticides	n farms both using coadjuvants
2008	1374	883	197	41	1231	647	386	11	250	166	72	9
2009	1352	882	225	35	1072	621	333	12	200	120	75	3
2010	1476	1071	281	44	1217	806	464	22	234	159	91	6
2011	1481	1118	325	63	1153	872	416	30	191	142	57	3
2012	1570	1230	330	54	1371	1048	543	20	209	176	72	4
2013	1379	1029	319	40	1454	1126	577	19	192	168	78	3
2014	1338	923	359	48	1362	1053	583	24	183	162	62	4
2015	1386	1007	397	44	1207	934	489	23	219	188	81	6
2016	1609	1168	440	66	1177	838	401	40	314	260	89	7
2017	1549	1025	458	44	1231	767	518	28	271	175	123	4
2018	1464	938	467	60	1337	895	477	33	298	180	136	8
2019	1371	875	436	43	1331	868	453	32	281	203	118	7
2020	1389	857	424	47	1303	816	614	38	296	188	145	9
2021	1416	879	458	57	1442	981	686	57	322	219	159	7

Table 7: Farms specialization (hectares devoted to the total) for durum wheat cropping in RICA.

threshold in% →	0	0	10	20	30	40	50	60	70	80	90
threshold 2ha →	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
year ↓											
2008	1822	1625	1555	1388	1160	944	662	459	325	214	138
2009	1646	1471	1397	1219	1028	807	554	390	249	166	109
2010	1803	1583	1520	1330	1108	878	631	431	301	215	144
2011	1745	1551	1467	1294	1085	809	555	386	253	157	101
2012	1878	1658	1584	1409	1180	909	623	428	283	191	132
2013	1684	1487	1407	1220	1027	762	484	338	219	143	84
2014	1587	1423	1357	1201	1012	741	467	304	203	145	91
2015	1595	1417	1345	1156	955	683	407	240	127	62	40
2016	1855	1656	1591	1375	1107	792	481	273	121	53	29
2017	1761	1523	1442	1243	979	681	391	217	99	51	32
2018	1716	1505	1419	1231	995	688	414	209	105	51	28
2019	1616	1391	1307	1107	870	593	338	196	86	35	21
2020	1646	1436	1349	1160	903	659	397	203	96	34	19
2021	1701	1514	1437	1235	981	700	408	223	99	42	23

wheat production, specifying that it uses 900 megajoules of `work; ag. tractors for growing win wheat, 2014 fleet, all fuels; 100-175HP - US-AR`. We then save this new process in a new database named `ecowheatal`

Table 8: Farms specialization (hectares devoted to the total) for soft wheat cropping in RICA.

threshold in % →	0	0	10	20	30	40	50	60	70	80	90
threshold 2ha →	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
year ↓											
2008	1596	1195	1081	783	522	331	193	122	85	59	35
2009	1405	1055	908	672	441	264	152	97	72	50	30
2010	1447	1066	939	696	489	332	200	117	72	47	25
2011	1344	1011	900	650	441	273	152	86	57	41	30
2012	1548	1192	1052	789	540	353	205	114	73	49	37
2013	1607	1254	1113	840	564	360	220	120	80	65	47
2014	1487	1155	1025	786	543	344	221	135	103	79	65
2015	1346	1043	926	657	418	271	149	81	52	33	24
2016	1320	1048	935	691	429	267	151	73	41	28	20
2017	1379	1061	931	682	426	242	124	61	35	22	13
2018	1519	1214	1063	763	492	305	165	88	42	27	16
2019	1487	1204	1051	757	483	283	135	79	35	21	14
2020	1455	1176	1035	769	513	316	172	91	54	30	18
2021	1607	1297	1162	881	601	336	178	86	53	26	20

Table 9: Farms specialization (hectares devoted to the total) for both durum and soft wheat cropping in RICA.

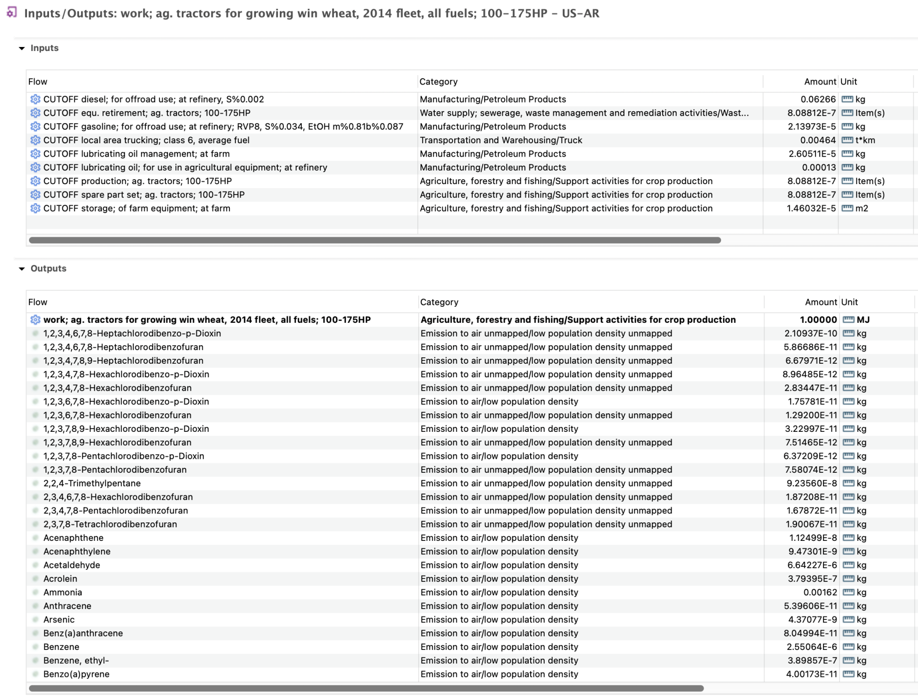
threshold in % →	0	0	10	20	30	40	50	60	70	80	90
threshold 2ha →	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
year ↓											
2008	281	269	266	243	188	146	84	51	34	21	10
2009	226	218	213	188	149	97	62	35	19	14	9
2010	250	244	235	211	169	107	65	31	19	9	5
2011	199	190	183	166	131	97	50	29	11	6	5
2012	219	214	208	185	150	96	49	24	12	5	2
2013	206	201	197	178	130	94	52	34	18	6	3
2014	193	188	185	168	136	93	53	30	15	6	2
2015	232	222	216	191	145	105	54	22	8	5	5
2016	320	313	306	279	212	150	63	29	13	4	1
2017	280	272	263	239	181	114	37	13	7	3	1
2018	335	330	315	281	222	150	76	29	12	5	3
2019	312	305	294	261	207	122	58	22	9	3	1
2020	326	319	307	277	217	131	64	27	12	3	1
2021	353	342	329	294	217	143	73	33	15	2	0

y through the following code:

```
#create a new dataset
ecowheatalydb = bd.Database("ecowheataly")
ecowheatalydb.register()
#create a new process called wheat_prod
wheat_prod=ecowheatalydb.new_activity(code = 'EcoWheataly production',
 name = "EcoWheataly production", unit = "ha")
#tell that 900 units of work of ag. tractor is used
wheat_prod.new_exchange(input=('usda_item','ccfa048cb86343798ac04f50a504c3af'),
 amount=900, unit="megajoule",type='technosphere').save()
wheat_prod.save()
```

Finally, we perform the LCA analysis:

```
import bw2calc as bc
functional_unit={ecowheatalydb.get('EcoWheataly production'): 1}
method_key=('IPCC 2013', 'Climate change', 'fossil from OpenLCA')
lca=bc.LCA(functional_unit,method_key)
lca.lci()
lca.lcia()
print(lca.score)
```



Inputs/Outputs: work; ag. tractors for growing win wheat, 2014 fleet, all fuels; 100-175HP - US-AR

Inputs

Flow	Category	Amount	Unit
CUTOFF diesel; for offroad use; at refinery, S%0.002	Manufacturing/Petroleum Products	0.06266	kg
CUTOFF equ. retirement; ag. tractors; 100-175HP	Water supply; sewerage, waste management and remediation activities/Wast...	8.08812E-7	Item(s)
CUTOFF gasoline; for offroad use; at refinery; RVP8, S%0.034, EtOH m%0.81b%0.087	Manufacturing/Petroleum Products	2.13973E-5	kg
CUTOFF local area trucking; class 6, average fuel	Transportation and Warehousing/Truck	0.00464	t*km
CUTOFF lubricating oil management; at farm	Manufacturing/Petroleum Products	2.60511E-5	kg
CUTOFF lubricating oil; for use in agricultural equipment; at refinery	Manufacturing/Petroleum Products	0.00013	kg
CUTOFF production; ag. tractors; 100-175HP	Agriculture, forestry and fishing/Support activities for crop production	8.08812E-7	Item(s)
CUTOFF spare part set; ag. tractors; 100-175HP	Agriculture, forestry and fishing/Support activities for crop production	8.08812E-7	Item(s)
CUTOFF storage; of farm equipment; at farm	Agriculture, forestry and fishing/Support activities for crop production	1.46032E-5	m2

Outputs

Flow	Category	Amount	Unit
work; ag. tractors for growing win wheat, 2014 fleet, all fuels; 100-175HP	**Agriculture, forestry and fishing/Support activities for crop production**	**1.00000**	**MJ**
1,2,3,4,6,7,8-Heptachlorodibenzo-p-Dioxin	Emission to air unmapped/low population density unmapped	2.10937E-10	kg
1,2,3,4,6,7,8-Heptachlorodibenzofuran	Emission to air unmapped/low population density unmapped	5.86686E-11	kg
1,2,3,4,7,8,9-Heptachlorodibenzofuran	Emission to air unmapped/low population density unmapped	6.67971E-12	kg
1,2,3,4,7,8-Hexachlorodibenzo-p-Dioxin	Emission to air unmapped/low population density unmapped	8.96485E-12	kg
1,2,3,4,7,8-Hexachlorodibenzofuran	Emission to air unmapped/low population density unmapped	2.83447E-11	kg
1,2,3,6,7,8-Hexachlorodibenzo-p-Dioxin	Emission to air/low population density	1.75781E-11	kg
1,2,3,6,7,8-Hexachlorodibenzofuran	Emission to air unmapped/low population density unmapped	1.29200E-11	kg
1,2,3,7,8,9-Hexachlorodibenzo-p-Dioxin	Emission to air/low population density	3.22997E-11	kg
1,2,3,7,8,9-Hexachlorodibenzofuran	Emission to air unmapped/low population density unmapped	7.51465E-12	kg
1,2,3,7,8-Pentachlorodibenzo-p-Dioxin	Emission to air/low population density	6.37209E-12	kg
1,2,3,7,8-Pentachlorodibenzofuran	Emission to air unmapped/low population density unmapped	7.58074E-12	kg
2,2,4-Trimethylpentane	Emission to air unmapped/low population density unmapped	9.23560E-8	kg
2,3,4,6,7,8-Hexachlorodibenzofuran	Emission to air unmapped/low population density unmapped	1.87208E-11	kg
2,3,4,7,8-Pentachlorodibenzofuran	Emission to air unmapped/low population density unmapped	1.67872E-11	kg
2,3,7,8-Tetrachlorodibenzofuran	Emission to air unmapped/low population density unmapped	1.90067E-11	kg
Acenaphthene	Emission to air/low population density	1.12499E-8	kg
Acenaphthylene	Emission to air/low population density	9.47301E-9	kg
Acetaldehyde	Emission to air/low population density	6.64227E-6	kg
Acrolein	Emission to air/low population density	3.79395E-7	kg
Ammonia	Emission to air/low population density	0.00162	kg
Anthracene	Emission to air/low population density	5.39606E-11	kg
Arsenic	Emission to air/low population density	4.37077E-9	kg
Benz(a)anthracene	Emission to air/low population density	8.04994E-11	kg
Benzene	Emission to air/low population density	2.55064E-6	kg
Benzene, ethyl-	Emission to air/low population density	3.89857E-7	kg
Benzo(a)pyrene	Emission to air/low population density	4.00173E-11	kg

Figure 8: A screenshot of the input-output tab in OpenLCA for the process `work; ag. tractors for growing win wheat, 2014 fleet, all fuels; 100-175HP - US-AR`.

The output of these commands is: 182.14, meaning that this farm produces 182.14 kg of CO2-Equivalent for each ha dedicated to wheat cropping.

A little more information is obtained as follows:

```
import bw2analyzer as ba
ca = ba.ContributionAnalysis()
for tmp in ca.annotated_top_processes(lca):
print(tmp)
```

whose output is

```
(182.14385993684303, 900.0,
 'work; ag. tractors for growing win wheat, 2014 fleet, all fuels;
 100-175HP' (MJ, None, 1 megajoule))
(0.0, 1.0, 'EcoWheataly production' (ha, GLO, None))
```

In addition, by running the code:

```
for tmp in ca.annotated_top_emissions(lca):
print(tmp)
```

it is straightforward to obtain the complete output:

```
(178.86719852685928, 178.86719852685928,
 'Carbon dioxide, fossil' (kilogram, None,
 ('air', 'low population density, long-term')))

(2.0280185872087184, 0.4992168804164976,
```

```
'Carbon monoxide, fossil' (kilogram, None,
 ('air', 'low population density, long-term')))

(1.1975288070802974, 0.0045223899633128894,
 'Dinitrogen monoxide' (kilogram, None,
 ('air', 'low population density, long-term')))

(0.051114015694737024, 0.001721010585242766,
 'Methane, fossil' (kilogram, None,
 ('air', 'low population density, long-term')))
```

7.3 Fertilizers

Winter wheat fertilization is primarily based on Nitrogen (N), Phosphorus (P), and Potassium (K) (more information in this web page).

The environmental effects of such mineral fertilizers are analyzed in Isherwood (1998). We summarize the content of Isherwood's article in the following table.

soil structure	**improves** makes soil more friable	$y_{nf} = 0.4 y_f$ y_f doesn't decrease over t
soil acidification	**worsens** due to N especially ammonium sulphate and to a lesser extent ammonium nitrate	can be corrected by lime
soil erosion	**improves** high yielding crops help to anchor the soil	Reduced tillage cultivation practices significantly reduce erosion
toxic elements	**don't know** Phosphate fertilizers can contain cadmium	Cadmium come from several Sources (atmospheric deposition from industrial processes, sewage sludges, animal manures)
water	**not relevant** In general the extent of N lost to water during the growing season is not linked directly to recent fertilizer applications.	major inputs are from nitrogen fixed by leguminous plant and animal wastes
eutrophication (algae multiplication)	**don't know** Due to P in inland water	potash has no known deleterious effect on the quality of natural waters

air (ammonia)	**don't know** Ammonia emissions from growing arable crops are low. Ammonia deposition contributes to acidification of soils. Nitrogen losses to the atmosphere in the form of ammonia following the application of urea can amount to 20more	West Europe 92% of all ammonia originates from agriculture. About 300,1 6 of the nitrogen excreted by farm animals is released to the atmosphere from farm animal houses, during storage, grazing and application of animal wastes to the soil
air (carbon dioxide)	**improves** Good fertilization and tillage management practices improve the net gain of carbon to the soil.	
air (nitrous oxide)	**improves** fertilizer management strategies that increase the efficiency of N uptake by crops are likely to reduce emission of N_2O to the atmosphere.	
air (methane)	**don't know** The direct impact of chemical fertilizers on methane emission is not clear.	emiisions due mainly to ruminant animals

Another interesting document concerning fertilizers is IFA and Systemiq (2022). The report points out that Nitrogen is the main cause of emissions (see in particular Chapter 1, paragraphs 6-11) and investigates how to improve its use efficiency (NUE).

To integrate mineral fertilization in our LCA, we build a process based on Appendix A of Brentrup et al. (2004). In particular, we take as reference the values for the 144 kg/ha case. After adapting the variable names to Brightway `biosphere3` database, the process has the following items:

```
202.9  'Phosphorus, 18% in apatite, 4% in crude ore' (
  kilogram, None, ('natural resource', 'in ground'))
889.8  'Granite' (kilogram, None,
  ('natural resource', 'in ground'))
47.12  'Coal, hard, unspecified'
  (kilogram, None, ('natural resource', 'in ground'))
2.285  'Coal, brown' (kilogram, None,
  ('natural resource', 'in ground'))
168.03  'Gas, natural'
  (standard cubic meter, None, ('natural resource', 'in ground'))
0.0129  'Methane, non-fossil'
  (kilogram, None, ('air',))
0.074  'Carbon monoxide, non-fossil'
  (kilogram, None, ('air',))
```

```
607.9  'Carbon dioxide, fossil' (kilogram, None,
  ('air', 'low population density, long-term'))
5.332  'Dinitrogen monoxide'
  (kilogram, None, ('air',))
3.534  'Ammonia'
  (kilogram, None, ('air',))
4.63  'Nitrogen oxides'
  (kilogram, None, ('air',))
0.553  'Particulate Matter, > 10 um'
  (kilogram, None, ('air',))
2.58  'Sulfur dioxide'
  (kilogram, None, ('air',))
0.041  'NMVOC, non-methane volatile organic compounds'
  (kilogram, None, ('air',))
1.483  'Nitrogen'
  (kilogram, None, ('water',))
0.016  'Nitrogen'
  (kilogram, None, ('water',))
0.104  'Phosphorus'
  (kilogram, None, ('water',))
0.0052  'Cadmium II'
  (kilogram, None, ('soil',))
144  application to N fertilizer use in winter wheat production systems
  (kilogram)
```

Moreover, we use the `Application of nitrogen fertilizer mix; at field - US` dataset from the University of Arkansas, available in the Federal LCA Commons. This dataset calculates emissions to air resulting from the application of 1 kg of nitrogen fertilizer in the US. These emissions are quantified according to IPCC Tier 1 methods for applied fertilizers in the US. In Figure 9, the screenshot of the input-output tab in openLCA for the selected process provides additional insight.

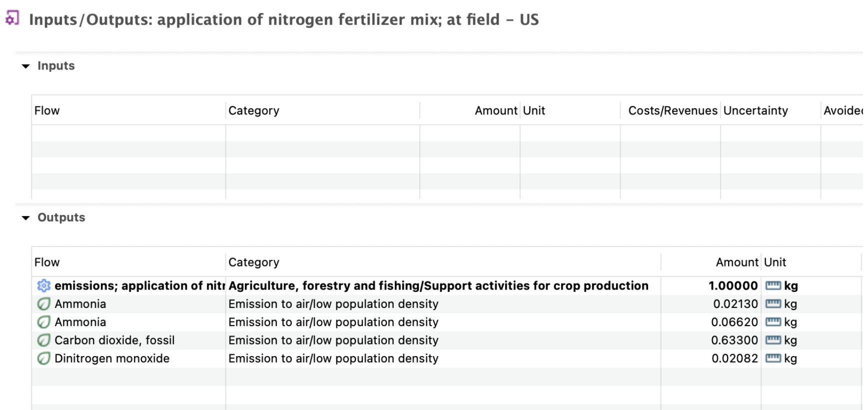


Figure 9: A screenshot of the input-output tab in OpenLCA for the process concerning the emissions to air resulting from the application of 1 kg of Nitrogen.

The `04_lca_import_N_fertilizers_use_process.py` script imports this process into Brightway. In particular, we apply the adapted version of Brentrup et al.'s process to a farm using 50 kg/ha of nitrogen. The LCA software then delivers the following results:

```
PERFORMING LCA #################################

functional unit

{'application to N fertilizer use in winter wheat production systems'
```

```
 (kilogram, None, None): 50}

Applied Brightway2 Method:
 IPCC 2013: climate change: global warming potential (GWP100) that delivered
 701.5157933155318 kg CO2-Eq

processes contribution

(701.5157933155318, 0.3472222222222222,
 'application to N fertilizer use in winter wheat production systems'
 (kilogram, None, None))

EMISSION CONTRIBUTION  ################################

(490.2477348348839, 1.8513888120651245,
 'Dinitrogen monoxide'
 (kilogram, None, ('air',)))

(211.07639736599393, 211.07639736599393,
 'Carbon dioxide, fossil'
 (kilogram, None, ('air', 'low population density, long-term')))

(0.12765625433530658, 0.004479166818782687,
 'Methane, non-fossil' (kilogram, None, ('air',)))

(0.06400486031870045, 0.02569444477558136,
 'Carbon monoxide, non-fossil'
 (kilogram, None, ('air',)))
```

7.4 Pesticides

The inclusion of a new chemical in the LCA involves analyzing a very complex system in which all possible pathways of the chemical molecule, from its use to its disappearance, must be considered.

As described in the report of Task 1.1, `Usetox` is the main tool used to evaluate the effects of chemicals Frantke (2019). Usetox aims to provide, for each chemical, characterization factors to assess its potential impact on two aspects: human health and the environment. This is done at both the midpoint and endpoint levels. Usetox outputs an *ad hoc* quantity called comparative toxic units (CTU). Characterization factors, therefore, transform quantities (kg) of active ingredients into CTU. Although already presented in the report of Task 1.1, for convenience, we also report here the table with the list of chemical products and their corresponding active ingredients (see Table 10).

Table 10: Names of chemical products and active ingredients composition.

type	tox level	active ing	product	quantity	concentration	active ing per ha
acaricida	irritante	sali di potassio degli acidi grassi	flipper	4-10l/ha	479,8g/l	1920-4800g/ha
anticrittogamico	prudenza	zolfo	cosavet df edge	3-8 kg/ha	80%	2400-6400g/ha
anticrittogamico	irritante	protioconazolo	pecari 300	0.65l/ha	300g/l	195g/ha
anticrittogamico	nocivo	Tebuconazolo	ares 430 sc	0.58l/ha	430g/l	250g/ha
diserbante	prudenza	Glifosate	clean-up	1-4-6-12l/ha	360g/l	360-4320g/ha
diserbante	irritante	2,4 D (sale)	pimiento 600	0.6-1.2l/ha	600g/l	360-720g/ha
diserbante	nocivo	MCPA (sale)	erbitox m pro	1.6-2l/ha	500g/l	800-1000g/ha
Fitoregolatore	irritante	clormequat	stabilan	2-3.5l/ha	461g/l	922-1613.5g/ha
Fitoregolatore	nocivo	Trinexapac etile	moddus	0.5l/ha	250g/l	125g/ha
Insetticida	irritante	Deltametrina	antal	0.3-0.5l/ha	25g/l	7.5-12.5g/ha
Insetticida	nocivo	Deltametrina	antal	0.3-0.5l/ha	25g/l	7.5-12.5g/ha
Insetticida	tossico	Pirimicarb	aphox 50	260g/ha	50%	130g/ha
Molluschicida	prudenza	Fosfato ferrico	ferrex	6kg/ha	25g/kg	150g/ha
Molluschicida	irritante	Metaldeide	luma-kl	7kg/ha	50g/kg	350g/ha

Finally, it is worth listing the Usetox methods that are present in Brightway:

```
('USEtox no LT', 'ecotoxicity no LT', 'total no LT')
```

```
('USEtox no LT', 'human toxicity no LT', 'carcinogenic no LT')
('USEtox no LT', 'human toxicity no LT', 'non-carcinogenic no LT')
('USEtox no LT', 'human toxicity no LT', 'total no LT')
('USEtox', 'ecotoxicity', 'total')
('USEtox', 'human toxicity', 'carcinogenic')
('USEtox', 'human toxicity', 'non-carcinogenic')
('USEtox', 'human toxicity', 'total')
```

7.5 Combining processes

Suppose now that the farm we are analyzing uses 900 megajoules of tractor power and 50 kg of nitrogen fertilizer per hectare of cultivated wheat.

7.5.1 Adding inputs to the wheat production process

We have already created the wheat production process in the machinery use section (Section 7.2). Recall that we first created a new database called `ecowheataly`. We then created the wheat production process with `new_activity` and added the `use of tractor` exchange to the process with `new_exchange`. We now add a new exchange for fertilizer use. Finally, we save the process in the database.

The updated code is as follows (note that we have simply added one line for the new exchange):

```
ecowheatalydb = bd.Database("ecowheataly")
ecowheatalydb.register()
wheat_prod=ecowheatalydb.new_activity(code =
 'EcoWheataly production', name = "EcoWheataly production", unit = "ha")
wheat_prod.new_exchange(input=
 ('usda_item','work; ag. tractors for growing win wheat, 2014 fleet, all fuels;
 100-175HP'),amount=900,unit="megajoule",type='technosphere').save()
wheat_prod.new_exchange(input=
('bentrup_item','application to N fertilizer use in winter wheat production
systems'),amount=50,unit="kilogram",type='technosphere').save()
wheat_prod.save()
```

7.5.2 Performing LCA

Now we are ready to perform our LCA using the following code, which is included in the `lca_machinery_fertilizers.py` script.

```
functional_unit={ecowheatalydb.get('EcoWheataly production'): 1}
method_key=('IPCC 2013', 'climate change', 'global warming potential (GWP100)')
lca=bc.LCA(functional_unit,method_key)
lca.lci()
lca.lcia()
```

7.5.3 LCA results

This farm produces about 883.66 kg CO2-Equivalent for each hectare of cultivated wheat. Of this quantity, 701.52 kg comes from the use of fertilizers, and 182.14 kg from the use of tractors. Details are given in the Brightway output reported below.

```
functional unit

{'EcoWheataly production' (ha, GLO, None): 1}
Applied Brightway2 Method: IPCC 2013: climate change:
global warming potential (GWP100) that delivered
883.6596532523748 kg CO2-Eq

processes contribution

(701.5157933155318, 0.3472222222222222,
 'application to N fertilizer use in winter wheat production systems'
 kilogram, None, 144 kg))

(182.14385993684303, 900.0,
 'work; ag. tractors for growing win wheat, 2014 fleet, all fuels;
 100-175HP' (MJ, None, 1 megajoule))
 (0.0, 1.0, 'EcoWheataly production' (ha, GLO, None))

EMISSION CONTRIBUTION  ################################
```

```
(490.2477348348839, 1.8513888120651245,
 'Dinitrogen monoxide' (kilogram, None, ('air',)))

(389.9435958928532, 389.9435958928532,
 'Carbon dioxide, fossil'
 (kilogram, None, ('air', 'low population density, long-term')))

(2.0280185872087184, 0.4992168804164976,
'Carbon monoxide, fossil'
(kilogram, None, ('air', 'low population density, long-term')))

(1.1975288070802974, 0.0045223899633128894,
'Dinitrogen monoxide'
(kilogram, None, ('air', 'low population density, long-term')))

(0.12765625433530658, 0.004479166818782687,
'Methane, non-fossil'
(kilogram, None, ('air',)))

(0.06400486031870045, 0.02569444477558136, '
Carbon monoxide, non-fossil'
(kilogram, None, ('air',)))

(0.051114015694737024, 0.001721010585242766,
 'Methane, fossil'
 (kilogram, None, ('air', 'low population density, long-term')))
```

7.6 Combining tractor use, fertilizers, and pesticides

Suppose now that we know the farmer applied a herbicide based on the active ingredient Pirimicarb. According to Table 10, we must add 130 g of this substance to our analysis. Therefore, for each hectare of cultivated wheat, the farm uses:

- 900 MJ of tractor power
- 50 kg of nitrogen
- 0.13 kg of Pirimicarb

To perform the inventory analysis, we must include the pesticide in the production process. Searching the `bisphere3` database, we find that Pirimicarb is among the available substances and is associated with the code `1c0699e2-9be2-4c30-8328-fc0ad8caac58`. Then, the following line is added to the wheat production input process:

```
wheat_prod.new_exchange(input=
('biosphere3','1c0699e2-9be2-4c30-8328-fc0ad8caac58'),
amount=0.13,unit="kilogram",type='biosphere').save()
```

Note the `type='biosphere'` assigned to the pesticide process, in contrast to the `technosphere` used for machinery and fertilizer. This choice reflects the fact that we did not include a production function for Pirimicarb. If we had modeled Pirimicarb in the technosphere, the result would have been a non-square inventory matrix. We therefore chose to assess the total ecotoxicity of Pirimicarb using the `('USEtox', 'ecotoxicity', 'total')` impact assessment method. Now, we have a measure of ecotoxicity in addition to the climate change one. The code for this analysis is provided in the `lca_machinery_fertilizers_pesticides.py` script.

```
The results of applying the methods are:
                                                                score        unit
IPCC 2013 climate change global warming potential (GWP100)  883.656135  kg CO2-Eq
USEtox     ecotoxicity     total                              59.109657        CTU
```

8 A full LCA implementation

8.1 The ReCiPe methodology

The recent literature on wheat LCA uses mostly the ReCiPe 2016 methodology. Jiang et al. (2021) compares wheat production under different fertilizing strategies using ReCiPe 2016. Xiong et al. (2024) perform a sustainability analysis of irrigated and rainfed wheat production systems under varying levels of nitrogen fertilizer using ReCiPe 2016. di Cristofaro et al. (2024) Evaluate the impacts of different wheat farming systems through LCA. They use a method developed by Recchia et al. (2019) that, according to the author, is a method based on ReCiPe 2008.Yu et al. (2024) forecast environmental impacts of smallholder wheat production by coupling LCA and machine learning, using a selected number of impact assessments from different institutions.

The ReCiPe 2016 methodology is described in Huijbregts et al. (2016, 2017). After an initial version released in 2008, the ReCiPe methodology was updated in 2016. While the 2008 characterization factors (CFs) refer to the European scale, the 2016 factors are representative of the global scale. Country- and continent-level factors are also provided for several impact categories. ReCiPe is, in fact, a set of impact assessment methods. The impact categories covered are listed in the left-hand column of Figure 10.

ReCiPe provides impact factors at both the midpoint and endpoint levels. At the midpoint level, each method yields a physical quantity representing, in general, the most damaging substance for the considered impact category. At the endpoint level, each method is associated with one of three areas of protection: human health, ecosystem quality, and resource scarcity. The damage to each of these three areas is measured as follows:

- Damage to human health is measured using the indicator “Disability Adjusted Life Years” (DALY), which expresses the time (in years) lost or lived with disability due to a disease or accident.
- Damage to ecosystem quality is measured as the number of local species lost per year.
- Damage to resource scarcity is quantified as the additional costs associated with future mineral and fossil resource extraction, expressed in U.S. dollars.

In the endpoint analysis, each of the methods listed on the left-hand side of Figure 10 provides a result expressed in one of these three units of measure. This enables a nested aggregation process that identifies damages to specific subsystems (see the middle column of Figure 10). Both midpoint and endpoint impacts are provided, where possible, under three different perspectives, whose characteristics are reported in Table 11.

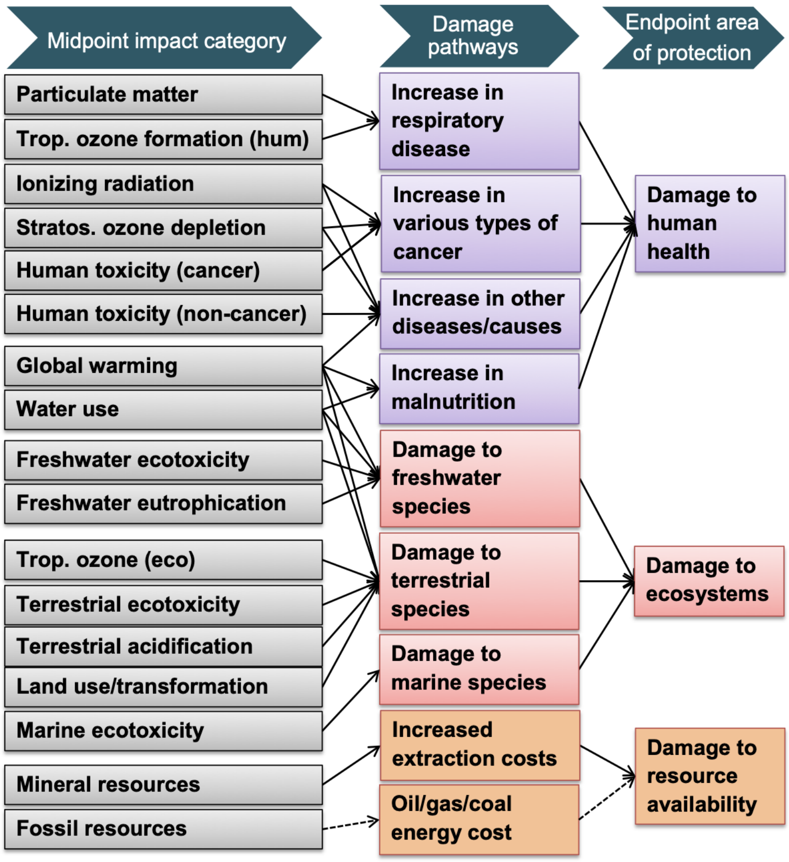


Figure 10: Overview of the impact categories that are covered in the ReCiPe2016 methodology and their relation to the areas of protection. Source: (Huijbregts et al., 2016, page 17).

8.2 ReCiPe in ECOWHEATALY

8.2.1 Regionalization

The following methods have country-specific impact factors:

- Fine dust formation
- Photochemical ozone formation - human health damage
- Photochemical ozone formation - ecosystem damage
- terrestrial acidification
- freshwater eutrophication

In Table 12, the midpoint CFs for Italy are distinguished from those of the non-regionalized methods.
Using the ratio between the values for Italy and those at the global level, we rescale all the CFs, i.e., endpoint and midpoint, under the different perspectives, for a more accurate evaluation of the Italian case.

Feature	Individualist Perspective (I)	Hierarchist Perspective (H)	Egalitarian Perspective (E)
Time Horizon	Short-term (typically 20 years)	Mid-term (typically 100 years)	Long-term (typically 500 years)
Value Choice	Focus on immediate impacts	Consensus-based, balanced approach	Precautionary, considering long-term risks
Uncertainty	Lower uncertainty due to short horizon	Moderate uncertainty	Higher uncertainty due to long horizon
Impact Emphasis	Proven and immediate effects	Scientifically agreed impacts	Potential future impacts, even if uncertain
Application of Country-Specific Factors	Less emphasis on regional detail	High emphasis on regional detail	May include regional detail, but broader focus
Relevance in Policy	Immediate policy relevance	Widely accepted for balanced policies	Long-term precautionary policies
Common Usage	Less common in LCIA	Default and most commonly used	Used for precautionary assessments
Examples of Use	Short-term projects, immediate regulations	General LCIA studies, standard policies	Sustainability planning, long-term strategies

Table 11: ReCiPe perspectives features

8.2.2 Pesticides

To evaluate pesticides, we query the `biosphere3` database for the active ingredients listed in Table 10. Some of these substances are not included in the database. The entries that are present are reported in Table 13, which also provides, as an example, the characterization factors (CFs) from the ReCiPe Ecotoxicity assessment method (Hierarchist perspective).

	PM2.5	NH3	Nox	SO2	NMVOC	P	PO_4^3-
Fine dust formation							
wwa	1	0.24	0.11	0.29			
Italy & co	2.02	0.65	0.22	0.28			
Photochemical ozone formation							
human health damage							
wwa			1		0.18		
Italy & co			1.13		0.57		
ecosystem damage							
wwa			1		0.29		
Italy & co			2.6		1.41		
terrestrial acidification							
wwa		1.96	0.36	1			
Italy		4.76	0.7	1.25			
freshwater eutrophication							
emitted to freshwater							
wwa						1	0.33
Italy						0.46	0.15
emitted to soil							
wwa						0.1	0.033
Italy						0.046	0.015
emitted to sea						0	0

Table 12: Midpoint CFs for Italy in ReCiPe 2016. (List of acronyms: wwa = world weighted average; Italy&Co=Italy, Malta, San Marino, Monaco; NH3=Ammonia; NO_x=nitrogen oxides; SO2=sulfur dioxide; P=Phosphorus; PO_4^3- Phosphate; NMVOC=Non Methane Volatile Organic Compounds.)

Type	tox level	Active Principle	terrestrial	freshwater	marine
Fungicide	harmful	Tebuconazole	0.091	1.833	0.152
Herbicide	caution	Glyphosate	0.0	0.351	0.008
Herbicide	irritating	2,4-D	0.042	0.359	0.02
Herbicide	harmful	MCPA	0.0	0.173	0.004
Growth regulator	harmful	Trinexapac-ethyl	0.429	0.456	0.011
Insecticide	harmful	Deltamethrin	1380.879	11.17	80.683
Insecticide	toxic	Pirimicarb	0.378	0.455	0.038
Molluscicide	irritating	Metaldehyde	45.466	0.068	0.007

Table 13: 'ReCiPe 2016', '1.1 (20180117)', 'Midpoint', 'Ecotoxicity', 'Hierarchist' unit: kg 1,4-DCB eq (DCB=Dichlorobenzene)

8.2.3 The set of LCIA methods

After evaluating the possibility offered by our dataset, we decided to assess the impact of the following aspects:

- Terrestrial Acidification
- Particulate Matter Formation
- Ozone Formation
- Freshwater Eutrophication
- Global Warming 100-year timescale

- Toxicity

As reported in Table 14, ozone formation is assessed using two methods: one evaluates the impact on human health, and the other evaluates the impact on the environment. Toxicity is addressed in greater detail by distinguishing between carcinogenic and non-carcinogenic effects on humans. The ecosystem impact category is also further refined to separately evaluate terrestrial and freshwater impacts.

Table 14 also provides details on units of measure and regionalization. As explained above, we use the information in Huijbregts et al. (2016) to derive Italy-specific impact assessment methods (the five methods listed in the top part of Table 14). The remaining impact assessment methods correspond to the original ReCiPe 2016 methods.

Method	Damage to	Geo CFs	Midpoint unit	Emitted to	Endpoint unit
Terrestrial Acidification	Ecosystems	Italy	kg SO2-eq	soil	species.year
Particulate Matter Formation	Humans	Italy	kg PM2.5-eq	air	DALY
Ozone Formation	Humans	Italy	kg NOx-eq	air	DALY
"	Ecosystems	Italy	"	air	species.year
Freshwater Eutrophication	Ecosystems	Italy	kg P-eq.	freshwater	species.year
Global Warming 100 year timescale	Humans and Ecoystems	Global	kg CO2-eq	air	DALY
Toxicity	Humans - Carcinogenic	Global	kg 1,4-DCB eq.	urban air	DALY
"	Humans - Non-carcinog.	Global	"	urban air	DALY
"	Ecosystems - Terrestrial	Global	"	industrial soil	species.year
"	Ecosystems - Freshwater	Global	"	freshwater	species.year

Table 14: Selected ReCiPe LCIA methods. (List of acronyms: SO2=Sulfur dioxide; PM=Particle matter; NOx=Nitrogen Oxides; P=Phosporus; CO2=Carbon Dioxide; DCB=Dichlorobenzene)

8.2.4 Example of LCA for an ECOWHEATALY farm

Method	Damage to	Geo CFs	Score	Unit	Score	Unit
Global Warming 100 year timescale	Humans and Ecoystems	Global	943.1366	kg CO2-eq	8.752307e-04	DALY
Toxicity	Humans - Carcinogenic	Global	1.1561	kg 1,4-DCB-eq	3.838143e-06	DALY
Toxicity	Humans - Non-carcinogenic	Global	0.2679	kg 1,4-DCB-eq	6.108489e-08	DALY
Particulate Matter Formation	Humans	Italy	2.6462	kg PM2.5-eq	6.250000e-11	DALY
Ozone Formation	Humans	Italy	3.3371	kg NOx-eq	3.036748e-06	DALY
Terrestrial Acidification	Ecosystems	Italy	15.9803	kg SO2-eq	3.387814e-06	Species.year
Ozone Formation	Ecosystems	Italy	7.6806	kg NOx-eq	9.908018e-07	Species.year
Freshwater Eutrophication	Ecosystems	Italy	0.0166	kg P-eq	1.114726e-08	Species.year
Toxicity	Ecosystems - Terrestrial	Global	185.9196	kg 1,4-DCB-eq	2.119483e-09	Species.year
Toxicity	Ecosystems - Freshwater	Global	0.0606	kg 1,4-DCB-eq	4.211711e-11	Species.year

Table 15: Results of LCA performed on a farm with data available in RICA and treated as described above in the text.

9 Conclusions

This report presented the methodological framework developed in Task 1.2 of the ECOWHEATALY project for performing Life Cycle Assessment (LCA) of wheat production systems. The main objective of the task was to establish the environmental assessment tools required to complement the economic and structural analysis of the Italian wheat sector developed in Task 1.1.

The analysis relied on farm-level information derived from the RICA/FADN database and on environmental inventory data available in existing LCA databases. Through the development of dedicated Python scripts, the relevant information was extracted and organized into a structured JSON database tailored to the needs of the ECOWHEATALY project. This data infrastructure makes it possible to link detailed farm management information with environmental impact assessment models.

Using this database, the report demonstrated how wheat production processes can be represented within a Life Cycle Assessment framework. The implementation in the Brightway2 software environment allows quantification of the environmental impacts associated with agricultural inputs, such as fertilizers, machinery use, and pesticides, using established life-cycle impact assessment methods.

Illustrative applications showed how the LCA framework can be used to estimate greenhouse gas emissions associated with wheat cultivation at the farm level. The results confirm that fertilizer use is a major source of emissions in wheat production systems, while machinery operations also contribute to overall environmental impacts.

An important methodological contribution of the report is the development of a matrix-based formulation of the LCA calculations. This formulation allows the environmental impact assessment to be integrated efficiently into the agent-based simulation model developed within the ECOWHEATALY project. By equipping agents with the matrices required for LCA calculations, the model avoids the computational bottlenecks that would arise from repeated database queries during large-scale simulations.

Overall, the results of Task 1.2 provide the environmental assessment infrastructure necessary for the next stages of the project. Combined with the farm typology and economic analysis developed in Task 1.1, the LCA framework will allow the ECOWHEATALY project to simulate and evaluate the environmental consequences of alternative agricultural policies and farming practices affecting the Italian wheat sector.

References

Brentrup, F., J. Küsters, J. Lammel, P. Barraclough, and H. Kuhlmann (2004). Environmental impact assessment of agricultural production systems using the life cycle assessment (LCA) methodology II. The application to N fertilizer use in winter wheat production systems. *European Journal of Agronomy 20*(3), 265–279.

di Cristofaro, M., S. Marino, G. Lima, and L. Mastronardi (2024). Evaluating the impacts of different wheat farming systems through life cycle assessment. *Journal of Cleaner Production 436*, 140696.

Frantke, P. (2019). Modelling the environmental impacts of pesticides in agriculture. In B. Weidema (Ed.), *Assessing the environmental impact of agriculture*, pp. 177–228. Cambridge, UK: Burleigh Dodds Science publishing.

Hauschild, M. Z., R. K. Rosenbaum, and S. I. Olsen (Eds.) (2018). *Life Cycle Assessment.Theory and Practice*. Springer Link.

Heijungs, R. and S. Suh (2002). *The Computational Structure of Life Cycle Assessment*. Springer Science.

Huijbregts, M. A. J., Z. J. N. Steinmann, P. M. F. Elshout, G. Stam, F. Verones, M. Vieira, M. Zijp, A. Hollander, and R. van Zelm (2016). ReCiPe 2016 A harmonized life cycle impact assessment method at midpoint and endpoint level Report I: Characterization. Technical Report RIVM 2016-0104, Dutch National Institute for Public Health and the Environment, Bilthoven, The Netherlands. https://www.rivm.nl/bibliotheek/rapporten/2016-0104.pdf.

Huijbregts, M. A. J., Z. J. N. Steinmann, P. M. F. Elshout, G. Stam, F. Verones, M. Vieira, M. Zijp, A. Hollander, and R. van Zelm (2017, Feb). Recipe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. *The International Journal of Life Cycle Assessment 22*(2), 138–147.

IFA and Systemiq (2022). Reducing emissions from fertilizers use. Technical report, Systemiq for International Fertilizer Industry Association (IFA). https://www.systemiq.earth/reducing-emissions-fertilizer/.

Isherwood, K. F. (1998). Mineral fertilizer use and the environment. Technical report, International Fertilizer Industry Association (IFA) and United Nations Environment Program (UNEP). https://digitallibrary.un.org/record/468871.

Jiang, Z., H. Zheng, and B. Xing (2021). Environmental life cycle assessment of wheat production using chemical fertilizer, manure compost, and biochar-amended manure compost strategies. *Science of The Total Environment 760*, 143342.

Recchia, L., A. Cappelli, E. Cini, F. Garbati Pegna, and P. Boncinelli (2019). Environmental sustainability of pasta production chains: An integrated approach for comparing local and global chains. *Resources 8*(1).

Su, D. (Ed.) (2020). *Sustainable Product Development. Tools, Methods and Examples*. Springet Nature.

Xiong, L., F. Shah, Y. Zhao, Z. Li, X. Zha, M. Ye, and W. Wu (2024). Sustainability analysis of irrigated and rainfed wheat production systems under varying levels of nitrogen fertilizer through coupling of emergy accounting and life cycle assessment. *Journal of Cleaner Production 447*, 141423.

Yu, C., G. Xu, M. Cai, Y. Li, L. Wang, Y. Zhang, and H. Lin (2024). Predicting environmental impacts of smallholder wheat production by coupling life cycle assessment and machine learning. *Science of The Total Environment 921*, 171097.

A Matrix computation of ECOWHEATALY LCA

This section is motivated by the failure encountered when attempting to use Brightway functions inside the agents of the ABM model.

The failure appears to be caused by Brightway?s need to read data from the database. When a considerable number of agents perform LCA simultaneously, the database becomes overloaded with queries. Some queries find the database busy with others, and the simulation stalls. This problem is particularly relevant for simulations running in parallel. The solution is to equip agents with the matrices required to perform the calculations, allow agents to customize them, and carry out the computations without querying the database.

We use Brightway to obtain the relevant matrices. Recall, in Table 16, the processes table of the LCA performed in the project. The table is produced by the script `git/prin_2022/ecowheataly_repast4py_model/brightway2/export_lca_matrices.py`. The values in the column `tractor use process` are taken from the USDA openLCA database. The values in the column `N use process` are taken from Brentrup et al. (2004).

The `wheat process` is defined according to the choices of each individual farm and therefore varies from farm to farm. The figures in the third column of Table 16 characterize the specific farm under consideration. Note that, in the table, a minus sign indicates that resources are used in the process, while a plus sign indicates that the item is an output of the process.

When computing the LCA of a single farm, we first assign the values in the `wheat process` column. The first three rows of Table 16 define the activities matrix $\mathbf{A}$. It is a square matrix describing the input?output relationships within the technosphere. In our case, it is a 3×3 matrix:

$$\mathbf{A} = \begin{matrix} 1 & 0 & -900 \\ 0 & 144 & -98 \\ 0 & 0 & 1 \end{matrix}$$

One might wonder why the farm has four production inputs while we consider only two in the technosphere. This is because we do not have detailed information on the production processes of 2,4-D (herbicide) and Deltamethrin (insecticide). These are therefore treated directly as outputs of the wheat production process. If, in the future, inventory analyses for these two active substances become available, we will have five production processes and a 5×5 $\mathbf{A}$ matrix.

The final demand vector used in this study is

$$\mathbf{f} = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$$

That is, we wish to assess the impact of producing 1 hectare of durum wheat. Solving the linear system

$$\mathbf{As} = \mathbf{f}$$

we obtain the scaling vector $\mathbf{s}^*$.

Now, we take the entries in the remaining rows of Table 16, corresponding to processes of type `biosphere`, and construct the biosphere matrix $\mathbf{B}$. In our case, this is a 54×3 matrix (see table 17). The biosphere quantities ($\mathbf{g}$) are obtained by multiplying the biosphere matrix by the scaling vector:

$$\mathbf{g}^* = \mathbf{B}\mathbf{s}^*$$

Afterward, we proceed to the LCIA phase by selecting the 10 impact assessment methods listed above. Using Brightway2, we obtain the characterization factors for the 54 biosphere elements considered and organize them into the 10×54 characterization matrix $\mathbf{C}$. The impacts are then calculated by multiplying the characterization matrix by the biosphere quantities:

$$\mathbf{h}^* = \mathbf{C}\mathbf{g}^*$$

Finally, we sum the elements of $\mathbf{h}^*$ having the same unit of measure to obtain the aggregate values of DALY and species loss.

As mentioned above, the data used for the calculations are exported using the script: `git/prin_2022/ecowheataly_repast4py_model/ brightway2/export_lca_matrices.py`

The script generates two CSV files, named `processes_data.csv` and `characterization_data.csv`. By reading the `processes_data.csv` file, one can obtain the $\mathbf{A}$ matrix from its first three rows and the $\mathbf{B}$ matrix from the remaining rows. Similarly, by reading the `characterization_data.csv` file, one can obtain the $\mathbf{C}$ matrix.

An example of the complete procedure is provided in the script

`git/prin_2022/ecowheataly_repast4py_model/brightway2/compute_inputs_and_lca_by_matices.py`.

It is also possible to compare these results with those obtained directly using Brightway2 by running the script:

`git/prin_2022/ecowheataly_repast4py_model/brightway2/compute_inputs_and_lca.py`.

type	name	tractor use process	N use process	wheat process
technosphere	Tractor power (MJ)	1.000000	0.000000	-900.000000
technosphere	Nitrogen (kg)	0.000000	144.000000	-98.000000
technosphere	wheat (ha)	0.000000	0.000000	1.000000
biosphere	1 'Coal, brown	0.000000	2.285000	0.000000
biosphere	2 'Coal, hard,	0.000000	47.119999	0.000000
biosphere	3 'Deltamethri	0.000000	0.000000	2.000000
biosphere	4 'Glyphosate'	0.000000	0.000000	0.000000
biosphere	5 'Granite' (k	0.000000	889.799988	0.000000
biosphere	6 'MCPA' (kilo	0.000000	0.000000	0.000000
biosphere	7 'Metaldehyde	0.000000	0.000000	0.000000
biosphere	8 'Phosphorus,	0.000000	202.899994	0.000000
biosphere	9 'Pirimicarb'	0.000000	0.000000	0.000000
biosphere	10 'Trinexapac-	0.000000	0.000000	0.000000
biosphere	11 'Acenaphthen	0.000000	0.000000	0.000000
biosphere	12 'Acetaldehyd	0.000007	0.000000	0.000000
biosphere	13 'Acrolein' (	0.000000	0.000000	0.000000
biosphere	14 'Ammonia' (k	0.001625	0.000000	0.000000
biosphere	15 'Ammonia' (k	0.000000	3.534000	0.000000
biosphere	16 'Benzene' (k	0.000003	0.000000	0.000000
biosphere	17 'Benzene, et	0.000000	0.000000	0.000000
biosphere	18 'Benzo(a)pyr	0.000000	0.000000	0.000000
biosphere	19 'Butadiene'	0.000000	0.000000	0.000000
biosphere	20 'Carbon diox	0.198741	607.900024	0.000000
biosphere	21 'Carbon mono	0.000000	0.074000	0.000000
biosphere	22 'Carbon mono	0.000555	0.000000	0.000000
biosphere	23 'Chromium II	0.000000	0.000000	0.000000
biosphere	24 'Chromium VI	0.000000	0.000000	0.000000
biosphere	25 'Dioxins, me	0.000000	0.000000	0.000000
biosphere	26 'Formaldehyd	0.000015	0.000000	0.000000
biosphere	27 'Manganese I	0.000001	0.000000	0.000000
biosphere	28 'Mercury II'	0.000000	0.000000	0.000000
biosphere	29 'Methane, no	0.000000	0.012900	0.000000
biosphere	30 'Methane, fo	0.000002	0.000000	0.000000
biosphere	31 'Nickel II'	0.000001	0.000000	0.000000
biosphere	32 'NMVOC, non-	0.000125	0.000000	0.000000
biosphere	33 'NMVOC, non-	0.000000	0.041000	0.000000
biosphere	34 'Particulate	0.000000	0.553000	0.000000
biosphere	35 'Propanal' (	0.000001	0.000000	0.000000
biosphere	36 'Propene' (k	0.000000	0.000000	0.000000
biosphere	37 'Styrene' (k	0.000000	0.000000	0.000000
biosphere	38 'Sulfur diox	0.000002	0.000000	0.000000
biosphere	39 'Sulfur diox	0.000000	2.580000	0.000000
biosphere	40 'Toluene' (k	0.000002	0.000000	0.000000
biosphere	41 'Xylene' (ki	0.000001	0.000000	0.000000
biosphere	42 'Cadmium II'	0.000000	0.005200	0.000000
biosphere	43 'Nitrogen' (	0.000000	1.499000	0.000000
biosphere	44 'Phosphorus'	0.000000	0.104000	0.000000
biosphere	45 'Tebuconazol	0.000000	0.000000	0.000000
biosphere	46 'Arsenic ion	0.000000	0.000000	0.000000
biosphere	47 '2,4-D dimet	0.000000	0.000000	5.000000
biosphere	48 'Dinitrogen	0.000005	0.000000	0.000000
biosphere	49 'Dinitrogen	0.000000	5.332000	0.000000
biosphere	50 'Nitrogen ox	0.001482	0.000000	0.000000
biosphere	51 'Nitrogen ox	0.000000	4.630000	0.000000
biosphere	52 'Gas, natura	0.000000	168.029999	0.000000
biosphere	53 'Particulate	0.000109	0.000000	0.000000
biosphere	54 'Particulate	0.000003	0.000000	0.000000

Table 16: An example of technosphere and biosphere items built for an Italian wheat farm.

B Biosphere references for ECOWHEATALY

short description	full description	biosphere3 code
1 'Coal, brown	'Coal, brown' (kilogram, None, ('natural resource', 'in ground'))	024c9722-1e88-412b-8c4b-10c532be8dca
2 'Coal, hard,	'Coal, hard, unspecified' (kilogram, None, ('natural resource', 'in ground'))	b6d0042d-0ef8-49ed-9162-a07ff1ccf750
3 'Deltamethri	'Deltamethrin' (kilogram, None, ('soil', 'agricultural'))	282973e4-3c2d-4a9c-a3f2-d39a5b36aa76
4 'Glyphosate'	'Glyphosate' (kilogram, None, ('soil', 'agricultural'))	3850d44e-8919-47bc-9c0a-51ccc4ec9d9f
5 'Granite' (k	'Granite' (kilogram, None, ('natural resource', 'in ground'))	a4375a18-172c-4f82-90b7-bca972f75548
6 'MCPA' (kilo	'MCPA' (kilogram, None, ('soil', 'agricultural'))	e5492922-eaf5-4409-aa49-7f2a35cd0336
7 'Metaldehyde	'Metaldehyde' (kilogram, None, ('soil', 'agricultural'))	597847df-518f-4bd6-ae50-1de01f2761a4
8 'Phosphorus,	'Phosphorus, 18% in apatite, 4% in crude ore' (kilogram, None, ('natural resource', 'in ground'))	9a7380d1-6e23-48ad-b35a-14bd1ecb3133
9 'Pirimicarb'	'Pirimicarb' (kilogram, None, ('soil', 'agricultural'))	1c0699e2-9be2-4c30-8328-fc0ad8caac58
10 'Trinexapac-	'Trinexapac-ethyl' (kilogram, None, ('soil', 'agricultural'))	51c7daf4-14e1-45e9-aa67-051c4ddcd9da
11 'Acenaphthen	'Acenaphthene' (kilogram, None, ('air', 'low population density, long-term'))	0555dc8e-d8b3-4da1-afaa-a2144758d590
12 'Acetaldehyd	'Acetaldehyde' (kilogram, None, ('air', 'low population density, long-term'))	55b0bc94-7f43-4930-ad57-25af3f892757
13 'Acrolein' (	'Acrolein' (kilogram, None, ('air', 'low population density, long-term'))	086f6b04-002c-49a0-9be8-2bad29a9c17a
14 'Ammonia' (k	'Ammonia' (kilogram, None, ('air', 'low population density, long-term'))	2b50f643-216a-412b-a0e5-5946867aa2ed
15 'Ammonia' (k	'Ammonia' (kilogram, None, ('air',))	87883a4e-1e3e-4c9d-90c0-f1bea36f8014
16 'Benzene' (k	'Benzene' (kilogram, None, ('air', 'low population density, long-term'))	8476d82a-4a17-4c08-8339-efd46c6518e7
17 'Benzene, et	'Benzene, ethyl-' (kilogram, None, ('air', 'low population density, long-term'))	e4ef0139-8f7a-4541-a2fb-8316558eb296
18 'Benzo(a)pyr	'Benzo(a)pyrene' (kilogram, None, ('air', 'low population density, long-term'))	32d98afc-e42b-46f6-b53e-9c949875ab20
19 'Butadiene'	'Butadiene' (kilogram, None, ('air', 'low population density, long-term'))	0315d855-dff2-44af-bb37-1b855df53d69
20 'Carbon diox	'Carbon dioxide, fossil' (kilogram, None, ('air', 'low population density, long-term'))	e259263c-d1f1-449f-bb9b-73c6d0a32a00
21 'Carbon mono	'Carbon monoxide, non-fossil' (kilogram, None, ('air',))	2cb2333c-1599-46cf-8435-3dffce627524
22 'Carbon mono	'Carbon monoxide, fossil' (kilogram, None, ('air', 'low population density, long-term'))	49c594c6-b6a8-42a3-95c5-cca812fda80b
23 'Chromium II	'Chromium III' (kilogram, None, ('air', 'low population density, long-term'))	6b29d83a-c43c-484c-8e73-474a8a22d71e
24 'Chromium VI	'Chromium VI' (kilogram, None, ('air', 'low population density, long-term'))	c2e854f9-fe22-4fe7-9083-cf6d0a8c7254
25 'Dioxins, me	'Dioxins, measured as 2,3,7,8-tetrachlorodibenzo-p-dioxin' (kilogram, None, ('air', 'low population density, long-term'))	e69dfe04-4b45-4e87-a6ce-08b1af61ca22
26 'Formaldehyd	'Formaldehyde' (kilogram, None, ('air', 'low population density, long-term'))	1258b87f-6a94-4c0f-a51a-cef98a3bf534
27 'Manganese I	'Manganese II' (kilogram, None, ('air', 'low population density, long-term'))	0af26a55-d357-469f-abad-8ced785cb4fb
28 'Mercury II'	'Mercury II' (kilogram, None, ('air', 'low population density, long-term'))	dc90db73-6f27-403d-baf1-cb7e0b6cae31
29 'Methane, no	'Methane, non-fossil' (kilogram, None, ('air',))	da1157e2-7593-4dfd-80dd-a3449b37a4d8
30 'Methane, fo	'Methane, fossil' (kilogram, None, ('air', 'low population density, long-term'))	f3bd723a-5276-4ae8-9860-b89537351a90
31 'Nickel II'	'Nickel II' (kilogram, None, ('air', 'low population density, long-term'))	c89873de-cd23-4323-a948-f5cfeebd2fc9
32 'NMVOC, non-	'NMVOC, non-methane volatile organic compounds' (kilogram, None, ('air', 'low population density, long-term'))	3f5339ef-1939-4f44-8cd6-98ac7584d456
33 'NMVOC, non-	'NMVOC, non-methane volatile organic compounds' (kilogram, None, ('air',))	d3260d0e-8203-4cbb-a45a-6a13131a5108
34 'Particulate	'Particulate Matter, ¿ 10 um' (kilogram, None, ('air',))	66020d27-7ae4-4e59-83a3-89214b72c40a
35 'Propanal' (	'Propanal' (kilogram, None, ('air', 'low population density, long-term'))	58f84a38-ca67-490c-8ed7-219c42dcc52d
36 'Propene' (k	'Propene' (kilogram, None, ('air', 'low population density, long-term'))	e9d5a946-70ac-4610-a95b-cc659b48f29e
37 'Styrene' (k	'Styrene' (kilogram, None, ('air', 'low population density, long-term'))	f7bdeabf-a11d-4ddb-ad19-501485f39f07
38 'Sulfur diox	'Sulfur dioxide' (kilogram, None, ('air', 'low population density, long-term'))	6ce44f77-d181-4396-8fa2-2276eeeb4c08
39 'Sulfur diox	'Sulfur dioxide' (kilogram, None, ('air',))	fd7aa71c-508c-480d-81a6-8052aad92646
40 'Toluene' (k	'Toluene' (kilogram, None, ('air', 'low population density, long-term'))	b98c02c6-89bb-4dd2-8d68-6af6758db3d9
41 'Xylene' (ki	'Xylene' (kilogram, None, ('air', 'low population density, long-term'))	c8214570-8e2d-4ccf-b9d7-aabc17068d4e
42 'Cadmium II'	'Cadmium II' (kilogram, None, ('soil',))	12d6029e-3801-42ee-a1bc-1ebf936884fc
43 'Nitrogen' (	'Nitrogen' (kilogram, None, ('water',))	dcfe0815-6fa3-4e1d-a55e-155b29904f1d
44 'Phosphorus'	'Phosphorus' (kilogram, None, ('water',))	2d4b8ec1-8d53-4e62-8a11-ebc45909b02e
45 'Tebuconazol	'Tebuconazole' (kilogram, None, ('soil', 'agricultural'))	a805071f-ce96-4d72-bdd5-4334d9aa3c23
46 'Arsenic ion	'Arsenic ion' (kilogram, None, ('air', 'low population density, long-term'))	ed751c30-a896-44f3-9a83-2a5328dde94d
47 '2,4-D dimet	'2,4-D dimethylamine salt' (kilogram, None, ('soil', 'agricultural'))	41a4e1fe-34ee-54d9-b049-3a60ada1ae3e
48 'Dinitrogen	'Dinitrogen monoxide' (kilogram, None, ('air', 'low population density, long-term'))	81305cda-63f1-4c1a-99c6-2c2568550ec4
49 'Dinitrogen	'Dinitrogen monoxide' (kilogram, None, ('air',))	20185046-64bb-4c09-a8e7-e8a9e144ca98
50 'Nitrogen ox	'Nitrogen oxides' (kilogram, None, ('air', 'low population density, long-term'))	9115356e-a534-4329-9ec6-d9208720241b
51 'Nitrogen ox	'Nitrogen oxides' (kilogram, None, ('air',))	c1b91234-6f24-417b-8309-46111d09c457
52 'Gas, natura	'Gas, natural' (standard cubic meter, None, ('natural resource', 'in ground'))	7c337428-fb1b-45c7-bbb2-2ee4d29e17ba
53 'Particulate	'Particulate Matter, ¡ 2.5 um' (kilogram, None, ('air', 'low population density, long-term'))	051aaf7a-6c1a-4e86-999f-85d5f0830df6
54 'Particulate	'Particulate Matter, ¿ 2.5 um and ¡ 10um' (kilogram, None, ('air', 'low population density, long-term'))	5716c728-bd33-414d-8691-16e5534f5d37

Table 17: A reference for biosphere processes.