**Analysing the resilience of agricultural production systems with ResiPy,**

**the Python production resilience estimation package**

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We present ResiPy, a Python object-oriented software to compute the annual production resilience indicator. This indicator can be applied to different anthropic and natural systems, e.g., agricultural production, natural vegetation and water resources to quantify their stabilities and estimate the risk of adverse events compromising the system under evaluation. We propose an illustrative application of ResiPy to agricultural production in Europe, expressed in economic terms. After estimating the single-country or single-crop resilience, we evaluate the overall resilience of diversified production systems, composed of different crops and different cultivation areas. ResiPy also includes a powerful graphical tool to visually estimate the impact of diversity on complex production systems. The robustness of the indicator and the simplicity of the code ensure its effective applicability in many fields and with different datasets.

Keywords: annual production resilience indicator, APRI, climate resilience, diversity, agriculture, commodity market, Python.

Software Metadata

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| Current software version v1.0 | Uploaded with manuscript |
| Legal Code License | EUPL v1.2 - GPL |
| Code versioning system used | None |
| Software code languages, tools, and services used | Python3 |
| Compilation requirements, operating environments & dependencies | numpy, statsmodels.api, pandas, itertools, matplotlib |
| If available Link to developer documentation/manual |  |
| Support email for questions | [matteo.zampieri@ec.europa.eu](mailto:matteo.zampieri@ec.europa.eu) |

Code Metadata

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| Current code version v1.0 | Uploaded with manuscript |
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**1. Introduction**

Climatological and hydrological disasters have grown by a staggering 3.5% per year since 1980 (Munich Re, NatCatSERVICE 2018, https://natcatservice.munichre.com/). Such disasters and extremes often distort fundamental physiological processes of plants thus affecting crop yields in terms of quantity and quality [1–3]. Following large-scale agroclimatic events, such as heatwave or drought, lower yields may also progressively give rise to sweeping socioeconomic repercussions upon seed prices, the value of crop production, farm income, and food security, to name a few. The implications of this cascade of events impacting global food security have given birth to various recent studies that contemplate detrimental effects of climate extremes on crop yields [4–6] and agricultural and food systems [7,8]. In a future scenario where climate change is increasingly colliding with major stressors of the global food system, such as population growth, environmental degradation, and trade interdependence, the risk of food-supply instabilities attributable to more frequent and intense climate extremes is expected to increase [7,9–11].

Among other factors, food security also relies on the resilience of agricultural commodity markets to shocks; that is, on the capacity of supply and demand (with or without human intervention by the market participants) to absorb disturbances triggered by extreme events while still producing and providing human food and animal feed without altering trade patterns. .

The definitions of resilience here considered refer to the ability of a production system to cope with perturbations to the state parameters yet maintaining its functions (ecological definition), or to recover quickly from such disturbances (engineering definition) [12–15]. These definitions are conceptually clear but they do not directly provide a practical way to measure resilience [16–18]. In fact, a quantitative estimation of resilience requires objective methods to identify and measure the amplitude of the disturbances [19]. Also as a result of such indeterminacy, a large number of indicators was proposed to measure different aspects of resilience [17,19–21].

For instance, the ability of land ecosystems to withstand environmental perturbations (i.e. ecological resilience) can be assessed by looking at the deviation from seasonal climatology of vegetation above-ground biomass and proxies such as the Normalized Differential Vegetation Index (NDVI) after an environmental disturbance [22–24]. Such operation can be conveniently conducted after normalizing the anomalies by the mean climatological values, in order to account for the ecosystem’s capacity to change [20].

The rate of return to the equilibrium state after a perturbation (i.e. engineering resilience) can be measured, for example by: the temporal autocorrelation of relevant vegetation variables [25]; the variance of the frequency spectrum of anomaly time series [26]; the spectral scaling component as given by the slope of the logarithm of the spectrum upon the logarithm of the reverse frequency [27,28]. Up to date, none of these methods has been used to evaluate agricultural production resilience.

The concept of resilience is closely connected to production stability [29–33]. Stability can be more easily evaluated from production time-series by the absolute or normalized variance [14], the latter being known as coefficient of variance. The coefficient of variance has been recently used to evaluate the effects of current climate variability on vegetation gross primary production [34–36]. Because of the discrete nature of agricultural production time-series (i.e. one value per year), this is the main aspect of resilience that is currently implemented [29,30,37–39].

. The annual production resilience indicator (Rp) is a simple and effective method to evaluate the production resilience of natural vegetation [40,41] and agricultural systems [33,42]. Rp is based on a function of the mean and the variance (as the coefficient of variation), thus it is formally a stability indicator. However, the particular functional form of Rp has been proved to be consistent with the ecological definition of resilience [32,33]. If stability is measured by the inverse coefficient of variation [29,30,39]:

1. *Sp = µ/ σ,*
2. n, then the annual production resilience indicator (*Rp*) can be defined as the squared stability [15,32,33]:*Rp = Sp2,*

This annual production resilience indicatorhas been already applied to annual agricultural production [32,33,42], vegetation primary production [40,41], and water resources [40]. Concerning agricultural production, Rp is inversely proportional to the risk of annual production losses over homogeneous production areas and increases with diversity. These and other properties of the annual production resilience indicator are summarized in Appendix A.

This article illustrates how *Rp* can be implemented to evaluate complex production systems taking the example of crop production in European countries. Crop production time-series often display non-stationarities such as trends and low-frequency variations that hinder the computation of *Rp* because *µ*and*σ* may be dependent on covariate(s)[33,42]. In this case, time-series need to be processed in such a way to filter out the low-frequency variability and isolate the annual production fluctuations whose amplitude and frequency can be related to resilience. This is usually performed byby applying smoothing procedures such as LOESS (locally estimated scatterplot smoothing)[43]: :

*(3) Pi = loess (pi),*

*(4) πi = pi / Pi*

*(5) σ' = std (πi)*

where {*pi}i=1,…,N* represents the production values of the time-series under evaluation, {πi} *i=1,…,N* are the normalized time-series with respect to the baseline values (i.e. the smoothed time-series {*Pi}*) and σ' is the standard deviation of the normalized time-series.

Since the mean of normalized time-series computed through *eqs. (3)-(5)* is close to one, the non-stationary production stability (i.e. the inverse coefficient of variation) can be defined as:

1. *S’p = 1 / σ'.*

Finally, the non-stationary crop production resilience indicator is given by the inverse squared standard deviation of the normalized anomalies [33,42], which is the squared non-stationary production stability:

*(7) R’p = S'p2.*

In case the production time-series is stationary, the baseline is constant and *R’p* is exactly equal to *Rp*(and *S’p*is equal to *Sp*).

In the next sections, we present a simple code that computes the annual production resilience indicator from non-stationary and diverse time-series and some examples of analysis that can be conducted to address the needs of different users, e.g. stakeholders, policy makers, and anyone interested in estimating the resilience of the agricultural production at the local, national and supra-national levels. This code can be easily adapted to any time-series of positively defined values.

**2. ResiPy Description: New Python 3 code for the annual production resilience estimation**

*ReciPy* is composed of the *ProSeries* class and some functions that are presented in the following frame:

|  |
| --- |
| **class** ProSeries:    # create production time-series  def \_\_init\_\_(self,name,p):  self.name = name  self.pro = p.copy()  self.x = p[year]  self.y = p[value]    # return length of the time-series  **def** length(self):  **return** len( list( self.x ) )  # compute average production  **def** mean(self):  **return** np.mean( self.y )    # return smoothed time-series  **def** smooth(self):  span=min( 20. / float( self.length() ), 1. )  x=np.array( self.x )  y=np.array( self.y )  z = sm.nonparametric.lowess( y, x, frac = span )  yl = z[:,1]  pl = self.pro.copy()  pl[value] = yl  **return** (pl)    # return normalized time-series  **def** norm(self):  yl = self.smooth()[value]  yn = np.divide( self.y, yl )  pn = self.pro.copy()  pn[value] = yn  **return** (pn)    # production stability  **def** p\_stab(self):  yn=self.norm()[value]  s=np.divide(1,np.std(yn))  **return**(s)    # production resilience = stability^2  **def** p\_res(self):  r=np.power(self.p\_stab(),2)  **return**(r)  # sum production time-series  **def** \_\_add\_\_(self,other):  proc = pd.merge( self.pro, other.pro, on=year)  pro2 = proc.drop( year, axis = 1)  pros = pro2.sum( axis = 1)  pro = pd.DataFrame( { year: list(proc[year]), value: list(pros) } )  names = self.name + ' + ' + other.name  **return** ProSeries(names,pro)    # copy time-series  **def** copy(self):  **return** ProSeries( self.name, self.pro.copy() )    # anomaly correlation between time-series  **def** acor(self,other):  a1 = self.norm()  a2 = other.norm()  proc = pd.merge( a1, a2, on = year )  proc.drop( year, axis = 1, inplace = True )  r = np.array( proc.corr() )[0,1]  **return** r  # plot time-series  **def** plot(self):  fig = plt.plot( self.x, self.y, label = self.name )  color = fig[-1].get\_color()  plt.plot( self.x, self.smooth()[value], label = '', color = color )    # compute diversified system resilience  **def** tot\_res(name, tss):  # tss is a list of ProSeries objects of a production system    # extract list of names  labels = list(map(lambda x : x.name, tss))    # compute mean individual productions  imeans = list(map(lambda x : x.mean(), tss))    # computes individual time-series resilience  ip\_res = list(map(lambda x : x.p\_res(), tss))  ip\_len = list(map(lambda x : x.length(), tss))    # compute progressively aggregated time-series  atss = list(it.accumulate(tss, lambda x , y : x + y))    # compute progressively aggregated time-series resilience  ap\_res = list(map(lambda x : x.p\_res(), atss))  ap\_len = list(map(lambda x : x.length(), atss))    # compute incremental anomaly correlation (Pearson) of the progressively accumulated time-series  pa\_cor = list(x.acor(y) for x, y in zip(atss[:-1], tss[1:]))  pa\_cor.insert(0,0.)    **return** labels,imeans,ip\_res,ap\_res,pa\_cor,ip\_len,ap\_len  # resilience-diversity plot  **def** res\_plot(totres,moreinfo=False, ylabel='mean production'):  # unpack variables  labels = totres[0]  imeans = totres[1]  ip\_res = totres[2]  ap\_res = totres[3]  pa\_cor = totres[4]  ip\_len = totres[5]  ap\_len = totres[6]    fig, ax = plt.subplots(figsize=(8,6))    #plot mean productions and pairwise correlations  color = (0., 1., 0., 1.)  if moreinfo:  llabels = list(it.starmap(lambda x, y, z : x + ' (' + str(y) + ',' + str(z) + ')', zip(labels,ip\_len,ap\_len)))  # provides a list of colors for correlations  cmap = mpl.cm.get\_cmap('jet')  pa\_col = list(map(lambda x : cmap((x+1)/2), pa\_cor))  pa\_col[0] = color  ax.bar(llabels,imeans, color=pa\_col, label='mean production')  else:  llabels = labels  ax.bar(llabels,imeans, color=color, label='mean production')  ax.set\_ylabel(ylabel)    # plot production resilience  ax2 = ax.twinx()  ax2.plot(llabels,ip\_res,'ko',label='individual resilience')  ax2.plot(llabels,ap\_res,'r-',label='incremental resilience')    plt.setp(ax.xaxis.get\_majorticklabels(), rotation=90)  # ask matplotlib for the plotted objects and their labels  lines, labs = ax.get\_legend\_handles\_labels()  lines2, labs2 = ax2.get\_legend\_handles\_labels()  ax2.legend(lines + lines2, labs + labs2, loc=0)    ax2.set\_ylabel('annual production resilience')    if moreinfo:  fig.tight\_layout(rect=[0, 0.03, 0.85, 0.95])  ax3 = fig.add\_axes([.875, 0.5, 0.025, 0.4])  norm = mpl.colors.Normalize(vmin=-1, vmax=1)  cb1 = mpl.colorbar.ColorbarBase(ax3, cmap=cmap, norm=norm, orientation='vertical')  cb1.set\_label('incremental anomaly correlation')  else:  fig.tight\_layout(rect=[0, 0.03, 1, 0.95])  return fig |

**Scripting details:**

*ProSeries* class consists of the time-series object creation with a label name and production time-series, which is passed through a pandas *DataFrame*, and includes several methods:

* *length:* it returns the number of years of the time-series.
* *mean:* it returns the production average of the time-series.
* *smooth*: it returns the smoothed time-series through eq. *(2)*. The *span* parameter of LOESS smoothing corresponds to 20 years, which is hardcoded in this initial version of the software. This value has been calibrated in previous studies [11,44].
* *norm:* it normalizes the production time-series, eqs. *(3)-(5)*.
* p\_stab: it computes production stability according to eq. *(6)*.
* *p\_res*: it computes the resilience indicator according to eq. *(7)* .
* *\_\_add\_\_*: it aggregates two time-series. The result is a time-series defined by the sum of the production in years when both individual time-series are defined.
* *copy*: it returns a shallow copy of the time-series.
* *acor*: it computes the correlation coefficient between two time-series.
* *plot*: it produces a plot of the original time-series and the smoothed one, both with the same colour.

The functions included in *ResiPy* are useful to analyze groups of time-series. Given a list of time-series, the function *tot\_res* returns all necessary information to characterize the total resilience of a diversified production system. These are the names, the (average) productions and the resilience of the individual time-series, the incremental resilience of the time-series obtained progressively summing the individual time-series (sorted by decreasing mean production), the incremental anomaly correlations between the time-series, the length of the individual and of the aggregated time-series. The function *res\_plot* produces a plot with all the information computed by *tot\_res* (if *moreinfo* is set to true) or just the average production and the resilience of the individual and aggregated time-series (if *moreinfo* is left false).

**3. Examples analyses**

**3.1 Data**

The case studies illustrated in this section are based on the freely available FAOSTAT data named ‘Value of Agricultural Production’. As an example, we use the csv file downloaded from the FAOSTAT website (www.fao.org/faostat/en) selecting the values of gross production for all crops in the European countries . According to the FAOSTAT grouping rule, the European countries set contains: Albania, Austria, Belarus, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, the Republic of North Macedonia, Norway, Poland, Portugal, Republic of Moldova, Romania, Russian Federation, Serbia, Serbia and Montenegro, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, and the United Kingdom.

Paraphrasing the FAOSTAT documentation (http://fenixservices.fao.org/faostat/static/documents/QV/QV\_e.pdf), the value of gross production has been compiled by multiplying gross production in physical terms by output prices at farm gate. Thus, value of production measures production in monetary terms at the farm gate level. Since intermediate uses within the agricultural sector (seed and feed) have not been subtracted from production data, this value of production aggregate refers to the notion of "gross production".

The unit of measure of the data provided by FAO is in millions of USD, taking years 2014-2016 as a reference. This implies that joint macroeconomic variability (i.e., the variability of all local exchange rates w.r.t. the USD) is subsumed into the European time series of agricultural production values. However, the *smooth* function would also contribute filtering out the low frequency variability of this effect anyway. Future analysis could consider the Eurozone more coherently by converting the time series in EUR. Alternative useful conversions, considering different crops, could be done in terms of energy (calories) or protein content [33]. However, the present paper aims at presenting some examples that can be easily replicated with publicly available data also for other regions of the world. Thus, no specific country selection, currency conversion nor any form of preprocessing is applied to the data downloaded from FAOSTAT.

Two examples of ResiPy application are given:

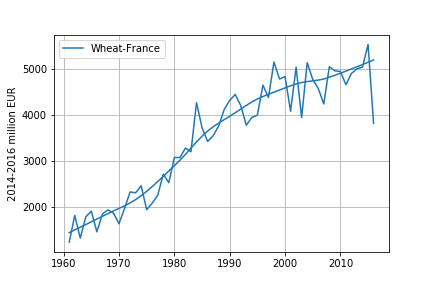
- resilience estimation for a single time-series or simple combination of them (Section 3.2) and

- resilience estimation for a diversified system production composed of different countries or different crops (Section 3.3).

**3.2 Individual and combined production resilience**

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| --- |
| **import** numpy **as** np  **import** pandas **as** pd  **import** statsmodels.api **as** sm  **import** csv  **import** matplotlib.pyplot **as** plt  **import** matplotlib **as** mpl  **import** itertools **as** it  # FAOSTAT data file  file = "FAOSTAT\_data\_3-15-2021.csv"  data = pd.read\_csv(file,sep=',')  # relevant columns' names and unit of measure  year = 'Year'  value = 'Value'  # column names for the crop and country selection  sel1\_name = 'Item'  sel2\_name = 'Area'  # select a random crop and country  sel1 = 'Wheat'  sel2 = 'France'  # define time-series name  name = sel1 + ' - ' + sel2  # define time-series production data  pro = data[data[sel1\_name]==sel1][data[sel2\_name]==sel2][[year,value]]  # create the object  ts1 = ProSeries(name,pro)  # call the methods  print( ts1.name, ': time series length = ', ts1.length(), ', P-res = ', '{:.0f}'.format( ts1.p\_res() ) )  ylabel = '2014-2016 million USD'  ts1.plot()  plt.legend()  plt.ylabel( ylabel ) |

The code reported above provides an example of basic use of the methods of the *ProSeries* class for wheat in France, which is the main European producer. The output of the print statement is: “Wheat - France : time series length = 56 , P-res = 97”. Figure 1 (plot from the package) allows a quick visual inspection of the time-series and of the anomalies with respect to the non-linear smoothing performed through the LOESS algorithm.

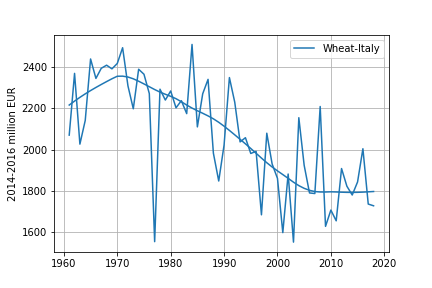


**Figure 1**: Production time-series of wheat in France expressed in equivalent 2014-2016 million USD, with the smoothed time-series used for the normalization. The annual production resilience value for this time-series is Rp=97.

Wheat production in France increased rapidly until the end of the 1990s, and then started stagnating [45]. This change point roughly corresponds to a climatic shift bringing warmer spring temperatures in France [46,47], which shortens the growing season reducing yields [44]. Variability increases as well in the recent decades. Worthy of notice are the effects of the 2003 heat wave [48], the 2016 yield loss for unfavorable weather conditions [44,49] and the effect of the 2018 drought that was perceived in the whole central and northern Europe [50]

The same analysis can be replicated for any agricultural production time-series in any country. For instance, it can be performed for Italy, another important European wheat producer.

|  |
| --- |
| # select another crop and country  sel1 = 'Wheat'  sel2 = 'Italy'  # same as before but define the time-series as “ts2”  # … |



**Figure 2**: As Figure 1, but for Italy. The resilience value for this time-series is Rp=138.

Wheat production in Italy decreased significantly since the 1970s to the 2000s. This negative trend can be attributed to reduction of sown wheat areas [42]. The largest loss happened in 1977. Large negative fluctuations are more frequent in the two most recent decades; an example of such event is year 2003, when heat wave significantly hampered growing conditions during sensitive stages in late spring [51]. However, the fluctuations compared to the baseline values are smaller than in France. In fact the annual production resilience indicator computed for Italy is larger than that one estimated for France.

Increasing production diversity using different crops with different climate sensitivity to spread the risk of unfavorable climate events, but also growing the same crop in different climatic regions, may represent effective measures to counteract the increase of extreme events and other negative effects induced by climate change. The effects of diversification on total crop production resilience can be quantified comparing the resilience of individual time series with the sum of the production time-series in different countries or for different crops in the same country. In the next example, we estimate the resilience of the aggregated Italian and French wheat production time-series.

|  |
| --- |
| # sum two time-series  ts3 = ts1 + ts2  ts3.plot()  print(ts3.name,': time series length = ',ts3.length(),', P-res = ', '{:.0f}'.format(ts3.p\_res()), ', correlation = ', '{:.2f}'.format(ts1.acor(ts2))) |

Immagine che contiene testo

Descrizione generata automaticamente

**Figure 3**: As Figure 1, but for the sum of productions in France and Italy. The resilience value for this time-series is Rp=159.

Figure 3 shows an example of incremental resilience, obtained by considering different climates and production values of wheat in France and Italy, which is higher than the individual countries’ production resilience. The output of the *print* statement gives: Wheat-France + Wheat-Italy : time series length = 56 , P-res = 159 , correlation = 0.33.

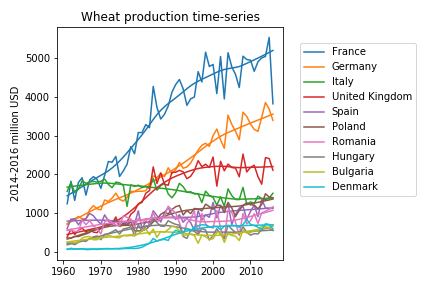
If two time-series are characterized by the same mean and variance, and are uncorrelated, the resilience of their sum is expected to double with respect to the individual ones [32,33]. The two time-series of this example are indeed only partially correlated, with Pearson correlation coefficient equal to 0.33. The resulting compensation effect is cancelling out some of the fluctuations. The contribution of Italian wheat is significant despite the lower mean production also because the Italian wheat resilience is larger than the French one. The next section shows analyses with greater complexity, involving more than two time-series.

**3.3 Total production resilience of diversified systems**

The *ResiPy* package can be used to quantify the overall production resilience of a single crop over different spatial units [42], or the resilience of a single production area growing different crops [33]. These are potentially complex analyses that can be easily achieved with the methods of the *ProSeries* class and the *tot\_res* and *res\_plot* functions.

Let us consider, for instance, the overall wheat production in Europe. The code in the following frame selects the relevant data for wheat in Europe. It sorts the countries from the larger to the smaller producer, limiting the number to a maximum of thirteen producers . Only time-series with at least 30 production years are considered in order to achieve a reasonable accuracy in the resilience estimation [32,33]. This selection filters out the Russian Federation, Ukraine and Czechia, leaving us with the top ten producers.

|  |
| --- |
| sel1\_name = 'Item'  sel2\_name = 'Area'  sel1 = 'Wheat'  # select wheat data  data2 = data[data[sel1\_name]==sel1]  # build up sorted list of maximum 15 time-series with at least 30 years of data  tss = []  min\_length = 30  sel2\_group = data2.groupby( sel2\_name ).mean()  sel2\_sort = sel2\_group.sort\_values( value, ascending=False).head(13)  for sel2 in sel2\_sort.index:  name = sel2  pro=data[data[sel1\_name]==sel1][data[sel2\_name]==sel2][[year,value]]  ts=ProSeries( name, pro )  if ts.length() > min\_length:  tss.append( ts )  ts.plot()  else:  print( sel2 )  plt.title( sel1 + ' production time-series' )  plt.ylabel( ylabel )  plt.legend( bbox\_to\_anchor = (1.05, 0.95) )  plt.tight\_layout() |

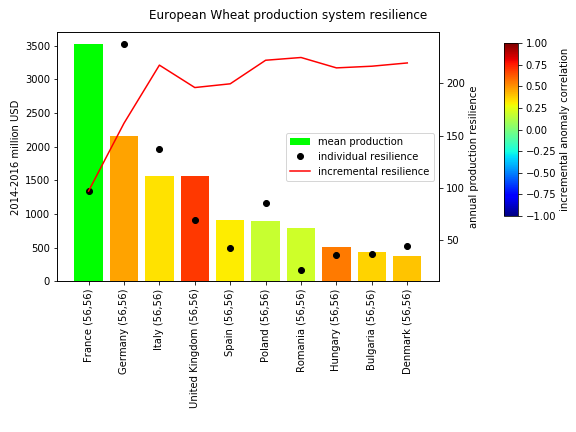


**Figure 4**: As Figure 1, but for the top ten European wheat producers.

The code presented above computes the resilience of the individual countries and of the incremental aggregation of the countries, which is useful to understand the effect of spatial variability on the total resilience of wheat production is Europe. The time-series of the top ten wheat producers is displayed in Figure 4. France is the most prominent producer followed by Germany, Italy and the United Kingdom.

The code in the following frame produces the “resilience-diversity plot” (Fig. 5), which is useful to understand the relative contribution of the different countries in building up the total resilience of wheat production in Europe.

|  |
| --- |
| # call the function computing system resilience  totres = tot\_res(sel1, tss)  # call the function producing the resilience-diversity plot  fig = res\_plot(totres, moreinfo=True, ylabel=ylabel)  fig.suptitle('European ' + sel1 + ' production system resilience') |



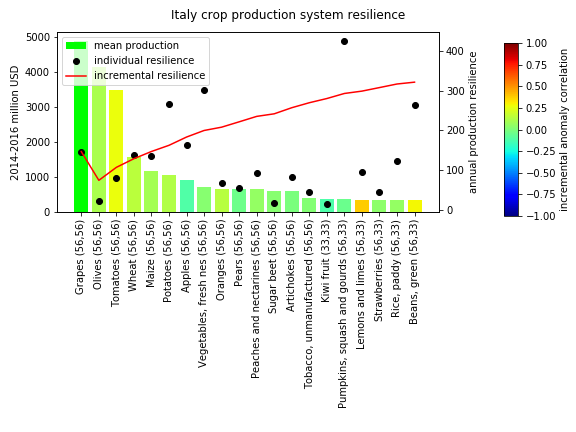
**Figure 5**: Individual (black dots) and incremental (red lines) wheat production resilience of the top ten European countries. Incremental production resilience is obtained by summing progressively the production time-series and computing the resilience from the sum of the production. The bar plot shows the average production of the different countries. The colors of the bars indicate the correlation coefficients between the production anomalies of each country and the sum of the previous countries in the sorted list. The two numbers in the x-labels correspond to the number of valid data in the individual time series and in the aggregated ones.

From the plot in Figure 5 it is possible to estimate the individual countries’ production wheat resilience as well as the effect of the spatial aggregation of national time-series on the total resilience of the European wheat production system. Among the top ten European producers, Germany displays the highest production resilience (above 200) followed by Italy, France and Poland. Romania shows the lowest estimated resilience.

The contribution of each country to the total resilience depends on the average production values. Cross-correlation between the different time series is modulating the effect of diversity on total resilience as well [32,33]. The production resilience of the top wheat producer (France) greatly increases when Germany and Italy – i.e. the second and third producers – productions are summed up. It is worth noting that cumulated resilience labelled as ‘Germany’ in Figure 5 is obtained summing the production of France and Germany. The cumulated resilience labelled as ‘Italy’ is obtained summing the Italian wheat production to that one of the previous two countries, and so on. The Italian production is only partially correlated to the sum of France and Germany. This explains the considerable increase in the resilience of the aggregated time-series [33] (see Appendix A). The United Kingdom resilience is characterized by lower resilience, and it is highly correlated to the sum of the first three countries. Thus, it does not bring positive contribution to the total resilience. All the other countries, characterized by lower individual resilience and lower value of production, contribute negligibly to the total wheat production resilience.

The effects of crop diversity on the crop production resilience of a specific country can be estimated by simply inverting the selection labels (see code block below) and then executing the same code reported in the last three blocks presented above. This simple modification yields the results shown in Figure 6.

|  |
| --- |
| sel1\_name = 'Area'  sel2\_name = 'Item'  sel1 = 'Italy'  # same as previous block  # … |



**Figure 6**: Same as Figure 5, but for the top twenty crops in Italy.

Grapes is, in economic terms, the primary crop in Italy (Fig. 6). Olives and tomatoes are not providing additional resilience with respect to grapes. This occurs due to the relatively high correlation between these three crops’ production times-series and because olives are characterized by lower production resilience.

The incremental resilience of the Italian crop production systems gradually increases when the other commodities are considered, even though they are characterized by lower production. The accuracy of the resilience estimation decreases when Kiwi production is considered, due to its shorter time-series (only 33 years are here considered).. The total resilience reaches its maximum when more than fifty crop are considered (not shown).

**5. Discussion and impact**

Despite the original ecological understanding of the resilience concept , currently, resilience is investigated in a rather long list of fields (i.e., economy, sociology, engineering, and law) [52,53]. In the last decade, in the scientific technical documents at both national and international level, its notion has been increasingly associated to that of climate change adaptation (CCA) and effectiveness of adaptation action (IPCC AR5, 2014).

While preventing damage and reducing losses in key sectors is paramount to ensure a successful transition towards climate-proofing natural and human systems (IPCC, Report “Global Warming of 1.5 °C”, 2018”), the relevance of resilience goes beyond, however, the context of ‘climate’ adaptation. It also strictly connects with the field of disaster risk reduction (DRR), which founding principles underlie preserving natural and human systems and ensuring a stable supply of ecosystem services that contribute to human well-being, in the face of ongoing shocks and stresses. In such a picture, strengthening resilience is therefore a high priority within both CCA and DRR. This is true especially in developing countries or in low-income countries generally showing a lower level of adaptive capacity despite being most exposed to threatening events. A particularly vulnerable sector to climate change is indeed a, which

A better understanding of resilience improves our knowledge of key socio-economic and natural systems, and enables taking *ad hoc* measures and/or designing strategies to diversify and minimize risks [54] . Despite the importance of resilience, providing practical advice to users (e.g. policymakers, managers, and farmers) remains a difficult task at present; scholars have often referred to resilience as a “too vague of a concept to be useful in planning” or in ecosystem management [55] .

*The ResiPy*software evaluate production and supportclimate resilience of agricultural production. Results from the selected examples stress the impact of having a highly diversified agricultural production system in stabilizing national food production [30,56]. In social-ecological systems, diversification can be accomplished through a variety of ways. In the agriculture sector, these include: crop diversification, changing production mix and strategies, changing technology, etc. While these are generally referred to as farm-level risk management strategies [57,58] we acknowledge their key role in enhancing agriculture resilience also at the macroeconomic level. Diversification has been often claimed to have a positive influence on economic resilience also, hedging people, sectors and nations against the risk of hazardous events [59].

The presented resilience analysis is in line with the objectives pursued by the DRR and acknowledged since the seminal papers of Markowitz [60] and Tobin [61]. Enhancing resilience and stability works therefore as a sort of insurance mechanism providing redundancy that can buffer (eco)systems against losses.

The *ReciPy* software description and the examples here shows allow an easy and fast replication of the similar analysis, e.g. focused on other areas of the world and/or considering other quantities. The graphical derivation of resilience further facilitates the assessment and interpretation of results, supporting decision-making in taking strategic decisions on risk diversification, adaptation action and ecosystem management.

The approach and the code are flexible enough to extend the resilience analysis to any (long-enough) time series with different time-scales, and in different contexts ranging from natural science to economy and society. Importantly, time series can be expressed in different units of measures: the same methodology can be applied to crop production time-series evaluated in terms of raw quantity [42] or caloric content [33], but alsoto natural ecosystem such as vegetation primary production [40] in order to evaluate the reliability of the related ecosystem services and of water resources. Furthermore, the use of the resilience indicator in monetary terms may be of great importance in comparing results of different systems provisions, across space and time. Accounting for the economic value of system production has, indeed, the additional advantage of capturing both the physical and socio-economical components of resilience in an integrated fashion.

All these aspects make the *ReciPy* software an important support tool for sectoral resilience analysis.

# *Conflict of Interest*

* *No conflict of interest exists:*

*We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.*

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