Reconciling the ecological and engineering definitions of resilience

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Abstract. Assessing and managing the human influence on the natural and anthropic ecosystems strongly demands for robust measures of their resilience, especially in a world facing global changes as it is the Earth now. Many definitions of resilience have been proposed in order to cover different contexts. However, they are mostly derived either from the ecological or the engineering definitions of resilience, which substantially differ between each other. Here, following the strategy for measuring the system perturbations by the return period of their impacts on production (or equivalently by the inverse frequency), I demonstrate the mathematical equivalence of the ecological and engineering definitions of resilience for a special class of production systems. These finding provides additional robustness to resilience assessments based on the recently proposed annual production resilience indicator.

Key words: agricultural resilience; annual production resilience indicator; crop production; ecological resilience; ecosystem resilience; engineering resilience; Holling; primary production; resilience.

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INTRODUCTION

The original Holling’s concept of ecological resilience ($R_{ecol}$) “determines the persistence of relationships within a system and is a measure of the ability of these systems to absorb changes of state variables, driving variables, and parameters, and still persist. In this definition resilience is the property of the system and persistence or probability of extinction is the result” (Holling 1973). Holling highlighted the occurrence of alternative and multiple states as opposed to the assumption of a single equilibrium and global stability; hence, resilience was “the size of a stability domain or the amount of disturbance a system could take before it shifted into an alternative configuration,” often leading to collapse of the original ecosystem structure due to sudden diseases outbreaks or other forms of competition (Holling 1973).

A different definition of resilience, used in engineering ($R_{engin}$), focuses of a single equilibrium and refers to the ability of a system to return to an equilibrium state after a temporary perturbation by measuring how quickly a system’s equilibrium is restored (Pimm 1984, Holling 1996). Both these definition have been highly influential and spread into different fields (Folke 2006, Brand and Jax 2007, Morecroft et al. 2012, Angeler and Allen 2016). A prominent example is the concept of socio-ecological resilience (Folke 2006), which contributed shaping the definition of resilience formally adopted by the Intergovernmental Panel on Climate Change (IPCC) as “the ability of a social or ecological system to absorb disturbances while retaining the same basic structure and ways of functioning, the capacity of self-organization, and the capacity to adapt to stress and change.”

While the ecological and the engineering definitions of resilience are conceptually clear, they do
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not directly provide a practical way to measure it (Morecroft et al. 2012, Quinlan et al. 2016). As a result, a univocal method to quantify resilience does not exist (Scheffer et al. 2015, Jones 2019). In fact, quantitative estimations of ecological and engineering resilience requires objective methods to identify and quantify the size of the perturbations (Meyer 2016). On the one hand, the ecological definition explicitly invokes a measure of the largest perturbation that a system can absorb (Holling 1973, 1996), which is clearly demanding for a quantification and a specific definition of the perturbation that might differ case by case, even for the same system (Seddon et al. 2016, Zampieri et al. 2017, Renard and Tilman 2019). On the other hand, a univocal estimation of the engineering resilience needs a quantification of the perturbation as well, because the restoring time that the system takes to reach the equilibrium after a shock plausibly increases with the amplitude of the perturbation (Scheffer et al. 2015, Simonovic and Arunkumar 2016). Since a single system in a specific equilibrium cannot be characterized by different resilience values, the restoring time needs to be somehow normalized by the amplitude of the perturbation (Meyer 2016, Simonovic and Arunkumar 2016). Thus, quantifying engineering resilience needs the definition and measurement of the perturbations as well.

A new framework to quantify the ecological resilience has been recently proposed for production systems (Zampieri et al. 2019b, 2020h). This framework consists of quantifying perturbation of different origins as well as compound events by the same measure, which is the return period—or the inverse frequency—of their impacts (see Methods). In this paper, I use this strategy to demonstrate the mathematical equivalence of the ecological and engineering definitions of resilience for linear productions systems characterized by a single equilibrium, which can therefore be measured by the same number. Such demonstration is presented in the Results section, while the Discussion section is devoted to the potential applicability of the presented outcomes to non-linear production system.

METHODS

Fig. 1 depicts a particular class of production systems characterized by an equilibrium state that is exactly coincident with the average environmental parameter value for which the maximum production is realized. In this condition, the system is perfectly adapted to the surrounding environment and climate. This representation can characterize the annual production statistics of a certain crop, or the primary production of a specific plant (or plant functional type) in a terrestrial environment, or of a specific organism in a marine environment. In this idealized view, the generic parameter can represent any state variable of the system, which for terrestrial ecosystems can be either energy, temperature, water, nutrients, for instance. Combinations of parameters could be accounted for by generalizing the same schematic in a multidimensional space. In any case, tipping points exist such that for perturbation larger than certain thresholds the system collapses and cannot produce any more. Albeit not explicitly represented in Fig. 1, other steady states might exist at lower potential values in other regions of the parameter space where the tipping points are exceeded. But, they are not interesting for the sake of the production core function of the system as the original organism might be extinguished or replaced by others as a result of competition.

Fig. 1 provides a visual example of a case for which the amplitude of the perturbations, their frequency, and their impacts of the ecosystem production follow two specific conditions allowing to measure the amplitude of the perturbances by the return period of their impacts. In fact, the shape of the parameter anomaly distribution depicted in Fig. 1 indicates that there is a strictly monotonic relationships between the amplitude of the perturbations and their rareness (first condition). Secondly, the shape of the production response to perturbations in Fig. 1 indicates that there is a strictly monotonic relationships between the amplitude of the perturbations and the production loss (second condition). The relationship between the spread of the distribution of the parameter anomaly and the range of normal functioning of the system imply that the years with optima or sub-optimal production are more frequent than the cases in which the production is zero or close to it. In fact, the gray areas below the red curve are smaller than the white area. For annual production systems such as agriculture (Zampieri et al. 2020a) or natural
ecosystems (Zampieri et al. 2019a) that are adapted to the local environmental conditions and climates, it is indeed sensible to assume that the largest perturbations are rarer compared to the “normal” conditions and that they result in larger impacts of the annual production values ($p$):

$$\Delta p = P - p$$  \hspace{1cm} (1)

where $\Delta p$ is the annual production anomaly, $P$ is the optimal production that would be achieve in absence of external stress of any magnitude, and $p$ is the actual production recorded in a certain year.

For a production system meeting these conditions, the perturbations can be measured by the reciprocal of the frequency, that is the return period of the production anomalies ($T^*$). $T^*$ is the expected average number of years that pass between production losses of same size (not to be confused with the restoring time to the equilibrium in the engineering definition of resilience). Using this strategy, the ecological resilience can be then simply measured by:

$$R_{eol} = T_{max}^*$$  \hspace{1cm} (2)

which is the return period of the largest perturbation that the system can absorb before losing completely the production ability ($p = 0$, $\Delta p = P$), which is inversely proportional to the area of the gray shaded regions in Fig. 1. This measurement strategy carries the advantage that it can be applied homogeneously to perturbations of different origins (and to combination of them) without the need of identifying them nor defining specific units of measure (but at the expense of losing the ability to isolate the effects of specific perturbations).

Fig. 1. Schematic of production system response to a random parameter perturbation around the equilibrium state. The red line represents the statistical distribution of the perturbations. The blue line represents the potential of the system. The black line represents the system production as a function of the anomalies of the state parameter. The red arrows represent examples of the system perturbations. For a small perturbation, the system does not lose its functioning capacity and tends to return to the equilibrium and to the optimal state providing relatively high production. This situation is represented by the black dot and arrow. For a larger perturbation (light red arrow) the system is pushed outside the range of functioning capacity, it cannot come back to the original state and it provides small or no production (gray dots and arrows). The gray areas correspond to the frequency of such extreme events.
For adapted productive systems, it has been shown that the ecological resilience (as defined by Eq. 2) is proportional to the annual production resilience indicator (Zampieri et al. 2019b, 2020b),

\[ R_{\text{ecol}} = \rho \times R_p \]  

that is given by:

\[ R_p = \frac{\mu^2}{\sigma^2} \]  

where \( \mu \) is the mean of the production time-series and \( \sigma \) is the standard deviation. A methodology to compute \( R_p \) from non-stationary time-series, where \( \mu \) and \( \sigma \) are not well-defined, is also available (Zampieri et al. 2020a). This allowed quantifying, for instance, the impact of diversity on complex agricultural systems (Zampieri et al. 2020b). While \( R_p \) has been derived in agricultural science, it has been applied to natural ecosystems as well (Zampieri et al. 2019a).

\( R_p \) is closely related to the coefficient of variance (CV = \( \sigma/\mu \)) which was also associated to natural vegetation (Paruelo et al. 2016, De Keersmaecker et al. 2017, Rudgers et al. 2018) and crop production (Zhang et al. 2015, Kahliluoto et al. 2019, Macholdt et al. 2019, Yang et al. 2019) resilience. However, \( R_p \) is a more consistent measure for resilience, as it is derived directly from the Holling’s ecological definition (Zampieri et al. 2019b). Moreover, \( R_p \) is easier to interpret as it is inversely proportional to the risk of production losses related to extreme events (Zampieri et al. 2019a, 2020a).

The next section shows, for a particular class of systems characterized by a linear relationship between \( T^* \) and the production losses, how this theoretical framework can embrace the engineering definition of resilience (\( R_{\text{engin}} \)) as well.

RESULTS

Fig. 2 depicts an idealized system where production accumulates linearly with time and responds proportionally to the amplitude of a perturbation, which is measured by the return period (\( T^* \)). \( \Delta p \) is the departure from the potential production (\( P \)) recorded at the end of the production cycle as a consequence of the perturbation that occurred during the production period.

The normalized value of the production anomaly is:

\[ \Delta p' = \frac{\Delta p}{P}. \]  

Let \( dt \) be the time that the system takes to return to the equilibrium after the shock and to recover the normal functioning conditions. No production takes place during this time. The restoring time \( dt \) can be normalized by the duration of the production period (\( \Delta t \)), or the growing season according to the terminology used in terrestrial ecosystems such as natural vegetation or crops:

\[ dt' = \frac{dt}{\Delta t}. \]  

Assuming a linear dependency between the production loss and that rareness of the event, the loss of production can be written as:

\[ \Delta p' = \frac{dp'}{dT^*} \times T^*. \]  

The first factor of Eq. 8 (\( dp'/dT^* \)) represents the derivative of the normalized production loss with respect to the normalized recovering time, which, under the linearity assumption, is equivalent to the ratio between the normalized production loss and the normalized recovery time. As a consequence of the assumption of linearity and of the normalization of the variables, this factor is constant and is equal to one because if the restoring time takes the entire production season (\( dt' = 1 \)), all the production is lost (\( dp' = 1 \)). So, this term can be eliminated by the equation, leading to:

\[ \Delta p' = \frac{dt'}{dT^*} \times T^*. \]  

The factor \( dt'/dT^* \) in Eqs. 8 and 9 is the derivative of the normalized recovering time with respect to the return period of the perturbation. Thus, it represents the dependency of the production system recovering time from the...
amplitude of the perturbation. This term is clearly linked to the engineering definition of resilience ($R_{\text{engin}}$):

$$R_{\text{engin}} = \left( \frac{dt'}{dT^*} \right)^{-1}. \quad (10)$$

In fact, according to Eq. 10, when considering systems that are subject to the same external forcing, the more resilient system will be the one that returns more quickly to the normal functioning. If $R_{\text{engin}}$ is infinite, the recovering is instantaneous ($dt' = 0$) and there is no loss of production.

Using Eqs. 9 and 10 and rearranging terms, $R_{\text{engin}}$ can be written as the ratio between the return period of the external forcing and the normalized production anomaly:

$$R_{\text{engin}} = \frac{T^*}{\Delta p'}. \quad (11)$$

Evaluating Eq. 11 for $T^* = T^*_{\text{MAX}}$ and $\Delta p' = 1$, one obtains:

$$R_{\text{engin}} = T^*_{\text{MAX}} = R_{\text{ecol}} \quad (12)$$

which is the ecological definition of resilience. Eq. 12 states that the ecological resilience and the engineering resilience can be quantified by the same number Q.E.D.

**DISCUSSION**

The theory presented above holds for a linear system that is subject to a perturbation. In reality, there can be many perturbations occurring during the production period (or growing season), or even continuous departures from the optimal conditions that last for long periods or for the entire growing season. In this case, the linear system integrates the different effects by summing...
up the impacts of the multiple shocks or the continuous stresses and the return period of the production loss automatically accounts for persistent and compound perturbation events. Thus, the theory holds just by considering the return period of the combination of shocks or of the persistent anomalies in the system parameters. This measurement strategy, however, is not able to select the effects of a specific perturbation. Additional indicators might be involved to isolate and analyze the different drivers of production resilience, if needed.

The assumption of linearity of the production cumulation during the season represents a strong limitation of case under study. In reality, the production rate might change during the season and the effects of the shocks can change as well (Barnabás et al. 2007, Gourdji et al. 2013, Rezaei et al. 2015, Webber et al. 2017). However, since the return period is computed on the production anomalies, measuring the ecological resilience is equivalent to weighting more the shocks and stresses occurring in the more productive or sensitive phases, which are necessarily rarer than those generally occurring in the whole growing season. So, the theory for the measurement of the ecological resilience consistently accounts for these non-linearities as well.

The assumption of linearity between the recovery time and the perturbation return period has not been actually used to reach the final result, but it deserves being discussed into some detail. On the one hand, the engineering resilience is ill-defined in case the derivative of the restoring time with respect to the return period is not constant (see Eq. 10), meaning that the engineering resilience is well-defined by a single number. The dashed lines depict two possible situations departing from the linear assumptions. In these cases, the engineering resilience of production system cannot be characterized by a single number. The red dot represents the state of the system where the ecological resilience is evaluated. In this situation, the ecological resilience is equivalent to the engineering resilience despite the possible non-linearities of the production system response to different perturbations.

Fig. 3. Simplified representation the dependency of the recovery time from the return period of the perturbation. The recovery time $dt$ is normalized by the length of the growing season $\Delta t$. The return period $T^*$ is normalized by the return period of the maximum perturbation that the system can absorb before losing completely the production capacity ($T_{\text{MAX}}^*$). Return periods larger than $T_{\text{MAX}}^*$ and recovery times larger than $\Delta t$ are accounted as well. The black line corresponds to the assumption of linearity between the two variables. In this case the engineering resilience is well-defined by a single number. The dashed lines depict two possible situations departing from the linear assumptions. In these cases, the engineering resilience of production system cannot be characterized by a single number. The red dot represents the state of the system where the ecological resilience is evaluated. In this situation, the ecological resilience is equivalent to the engineering resilience despite the possible non-linearities of the production system response to different perturbations.
resilience of a specific systems cannot be quantified by a single number in the presented framework. Let’s consider, for instance, a situation in which the restoring time is smaller for perturbations smaller than $T^{*}_{\text{MAX}}$ and larger for those larger than $T^{*}_{\text{MAX}}$ with respect to the linear relationship, or a situation where the opposite occurs. These situations are depicted in Fig. 3. In these cases, engineering resilience cannot be univocally quantified, as also acknowledged in other studies (Morecroft et al. 2012, Scheffer et al. 2015, Quinlan et al. 2016). On the other hand, the ecological definition leads to a well-defined quantity because it is evaluated for a specific combination of $T^{*}$ and $dt$ (red dot in Fig. 3). This represents a superior aspect of the ecological definition of resilience with respect to the engineering one. When $T^{*}$ equals $T^{*}_{\text{MAX}}$, the ecological and engineering measures of resilience coincide even though the ratio between $dt$ and $T^{*}$ varies. Therefore, the equivalence between the ecological and the engineering definitions of resilience is verified either in the case that the recovery time is proportional to $T^{*}$, or alternatively in the case that the engineering resilience is evaluated for $T^{*}$ equal to $T^{*}_{\text{MAX}}$.

**Conclusions**

Robust resilience measurements allow evaluating how ecosystems respond to the increasing pressures connected to the anthropic influence on the environment and on the climate system and how much society will risk losing important ecosystem services such as agricultural production. For this purpose, the annual production resilience indicator ($R_{p}$) was recently proposed to support resilience assessments ecosystem primary production and related services such as food production.

Assuming that the perturbations of a production system around a specific equilibrium state can be measured by the return period of their impacts, this paper demonstrates the quantitative equivalence of the ecological and engineering definitions of resilience. While the demonstration is provided only for a special idealized case, the presented theory can hold also for more general classes of production systems.

This outcome adds robustness to the recently proposed annual production resilience indicator, which was derived from the ecological definition of resilience under the theoretical framework presented here and it is therefore consistent with the engineering definition of resilience as well.

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