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Modelling the Demand for Weather Index-Based Insurance Products in Regions Prone to Agricultural Droughts

Dmitry V. Kovalevsky
Climate Service Center Germany (GERICS), Helmholtz-Zentrum Geesthacht (HZG)
Fischertwiete 1, 20095 Hamburg, Germany
e-mail: dmitrii.kovalevskii@hzg.de

María Máñez Costa
Climate Service Center Germany (GERICS), Helmholtz-Zentrum Geesthacht (HZG)
Fischertwiete 1, 20095 Hamburg, Germany
e-mail: maria.manez@hzg.de

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Abstract

Weather index-based insurance is a promising insurance scheme that might be particularly relevant for the agricultural sector in many developing countries. In particular, it might be efficient in regions prone to agricultural droughts. Weather index-based insurance policies might be more affordable to farmers, as the payouts in these insurance schemes are based on weather indices objectively determined for the specific agricultural regions, and therefore the costly individual loss assessment is not necessary. We develop a stochastic model to simulate the demand for insurance policies in a drought-prone region. For the proposed modelling approach, it is essential that weather and climate services provide forecasts of the weather index on which the insurance scheme is based, as tailored products for regions vulnerable to droughts. In such a case, among other factors, the demand for the insurance policy might depend on the skill of available seasonal weather forecast, from which the weather index forecast is derived. We compare different strategies of individual farmers regarding weather index-based insurance products. One of the findings of this modelling study is that decisions based on a forecast for the coming season with very low skill might provide less economically successful strategies for the farmers than the decisions made when the forecast is ignored or is unavailable. Therefore, presented modelling results suggest that both strategies of individual farmers and the dynamics of aggregate demand for insurance policies might be sensitive to the skill of available regional forecast.

1 Introduction

Agriculture is considered to be the economic sector most vulnerable to climate change, and in many regions, weather- and climate-related risks for agricultural sector are dramatic. Crop insurance is an important mechanism of agricultural risk transfer, but, in general, it is often expensive and unaffordable to many farmers, especially in developing countries. One of the reasons for why the crop insurance premiums are so high is the expenditures for loss assessment. In weather index-based insurance schemes the payouts are based on weather index objectively determined for the specific agricultural region, and therefore the individual loss assessment is not necessary. This paves the way to cheaper and more affordable agricultural insurance [The World Bank, 2011].

Assessments of historical impacts of hazardous events throughout the 20th century suggest that droughts have had the greatest negative impacts of all natural hazards [Mishra and Singh, 2010]. In many regions of the world, droughts have huge impacts on agriculture, and, not surprisingly, the agricultural drought (defined as the decreased availability of moisture for crops) enters the standard drought classification as one of few basic drought types [Burke et al., 1994]. Insurance from drought is one of the more promising types of weather-index based insurance.

In the present paper, we argue that the strategies of individual farmers in a region prone to agricultural droughts regarding the weather index-based insurance might be substantially influenced by the availability of weather index forecasts for the region. The latter might be derived from seasonal weather forecasts. A weather index forecast is one possible product of weather/ climate services [Preuschmann et al., 2017, van den Hurk et al., 2016] tailored to the specific drought-prone region.

The rest of the paper is organized as follows. In Sec. 2 we briefly describe a model of weather index-based insurance. In Sec. 3 we introduce a simple statistical model connecting the actual weather index (on which the payouts of weather index-based insurance are based) to the forecasted weather index (that, generally, might be derived from seasonal weather forecasts and might represent one of weather/ climate services tailored for the region under study). Sec. 4 introduces three different strategies of individual farmers with respect to buying the insurance policies and presents the numerical simulations of farmers' income dynamics under these strategies. In Sec. 5 simple models of the dynamics of aggregate demand for weather index-based insurance policies are introduced. Sec. 6 concludes.

2 Model of weather index-based insurance

The model of weather index-based insurance presented below is largely based on a model described in [Conradt et al., 2015]. However, we brought certain modifications to the model to fit it better to the purposes of the present study.

A key variable for our study is the weather index WI. The weather index aggregates the weather information within the vegetation period. This might be a rather simple index, e.g. based on precipitation only, or a more complex construct. It should be stressed that in real-world applications WI is a region- and crop-specific variable [Conradt et al., 2015].

Let $WI_{\mathrm{A},t}$ be the actual value of weather index at time t (in the context of our study, yearly time step is chosen, so t enumerates the year). In the rest of the present section, the subscript t will be omitted, and the actual weather index will be denoted simply as WI_{A}.

In general, WI_{A} is derived from one or several weather or climate variables, that, in turn, are controlled by complex regional weather and climate dynamics. However, for our purposes we make a simplification and model WI_{A} as an uncorrelated random process with a uniform probability density function (PDF):

$$\pi(WI_{\mathrm{A}}) = \begin{cases} \frac{1}{WI_{\max}-WI_{\min}}, & \text{if} \quad WI_{\min} < WI_{\mathrm{A}} < WI_{\max}, \\ 0, & \text{otherwise,} \end{cases} \tag{1}$$

where $WI_{\min}$ ($WI_{\max}$) is the minimum (maximum) possible value of WI_{A}, respectively.

Crop yield y is supposed to depend on WI_{A} only,

$$y = g(WI_{\mathrm{A}}). \tag{2}$$

Often, a random term is added to the r.h.s. of Eq. (2), to account for the factors additional to weather conditions that affect crop yield. However, in the simple model developed for the present study, this random term will be omitted.

Specifically, we define the functional dependence $g(\cdot)$ in the r.h.s of Eq. (2) as

$$y = WI_{\mathrm{A}}^{\beta}, \qquad \beta = \text{const.} \tag{3}$$

With the PDF defined by Eq. (1), the average crop yield

$$\bar{y} = \int y(WI)\pi(WI)d(WI) \tag{4}$$

is equal in this case to

$$\bar{y} = \frac{1}{\beta+1} \cdot \frac{WI_{\max}^{\beta+1} - WI_{\min}^{\beta+1}}{WI_{\max} - WI_{\min}}. \tag{5}$$

Following the concept of weather index-based insurance, the payout PO in the current year depends on the realization of WI_{A} in that year and is equal to

$$PO(WI_{\mathrm{A}}) = \gamma \cdot \max(0, S - WI_{\mathrm{A}}), \tag{6}$$

where γ is a constant scaling factor called the tick size, and S is the strike level – the threshold at which the payout is triggered. Specifically, one might assume that

$$S = \xi \cdot WI^{*}, \tag{7}$$

where ξ is a constant scaling factor ($0 < \xi < 1$) and WI^{*} is the level of the weather index corresponding to the average crop yield (Eq. (4)),

$$WI^{*} = g^{-1}(\bar{y}). \tag{8}$$

If the crop yield is parameterized by Eq. (3), the strike level can be expressed as

$$S = \xi \bar{y}^{1/\beta}. \tag{9}$$

The actuarially fair insurance premium P should be equal to average payout:

$$P = \int PO(WI)\pi(WI)d(WI). \tag{10}$$

In our case,

$$P = \frac{(S - WI_{\min})^2}{2(WI_{\max} - WI_{\min})}. \tag{11}$$

3 Model of forecast-based weather index

We now assume that a seasonal weather forecast is available for the region under study, and that, in general, a forecast of the weather index for the coming season might be made on the basis of that seasonal weather forecast (this might be one of the weather/ climate services tailored for the region).

Let $WI_{\mathrm{F},t}$ be the value of weather index at time t derived from seasonal weather forecast for period t. In general, estimating $WI_{\mathrm{F},t}$ might be a challenging task. What interests us now, however, is the relation between the forecast-based weather index $WI_{\mathrm{F},t}$ and the actual weather index $WI_{\mathrm{A},t}$. Obviously, the skill of forecasting the weather index should depend on the skill of the available seasonal weather forecast. For the purposes of our study we make another one huge simplification and assume the relation

$$WI_{\mathrm{F},t} = WI_{\mathrm{A},t} + \Delta + \varepsilon_t, \tag{12}$$

where Δ is the constant systematic error and ε_t is a random error. Our assumption regarding ε_t is that it is an uncorrelated random process with a uniform PDF

$$\pi(\varepsilon_t) = \begin{cases} \frac{1}{2B}, & \text{if} \quad -B < \varepsilon_t < B, \\ 0, & \text{otherwise}, \end{cases} \tag{13}$$

where $\pm B$ are the bounds of the random error. The statistical relation (12) of forecasted to actual weather index is illustrated in Fig. 1. One of the possible realizations of random dynamics of actual weather index is depicted by a blue line. As defined by Eq. (1), the actual weather index is simulated as an uncorrelated random process with uniform distribution. Its upper and lower bounds ($WI_{\max}$ and $WI_{\min}$) are depicted by horizontal light-grey and dark-grey line respectively. The forecasted weather index is related to the actual weather index through a statistical model (12), one of the possible realizations is depicted by a red line. For this numerical example, a rather large positive systematic error Δ is chosen, and an uncorrelated random error also has a remarkable standard deviation. The critical level of the weather index defined by Eq. (17) (see Sec. 4 below) is also depicted on Fig. 1 (horizontal green line).

4 Strategies of individual farmers

Below we explore three different strategies of individual farmers who have to make a decision on whether to buy an insurance policy for the coming year or not.

'No forecast' case. In this case, we assume that the weather index forecast is either unavailable to the farmer or is ignored, and the farmer always buys the insurance policy.

Let I_t be the farmer's income in year t. Under this strategy,

$$I_t = y(WI_{\mathrm{A},t}) + PO(WI_{\mathrm{A},t}) - P \qquad \text{for all} \quad t. \tag{14}$$

We also define CI_t — the farmer's cumulated income by year t, as a sum

$$CI_t = \sum_{k=0}^{t} I_k. \tag{15}$$

'Perfect forecast' case. We now assume that the farmer makes their decision on the basis of the weather index forecast. Moreover, for didactic purposes, we make an

assumption that the forecast is perfect, i.e. that the forecasted value of the weather index is always equal to its actual value:

$$WI_{\mathrm{F},t} \equiv WI_{\mathrm{A},t} \qquad \text{for all} \quad t. \tag{16}$$

In case of the statistical model defined by Eq. (12), this would mean that $\Delta = 0$, $\varepsilon_t = 0$.

What would be the farmer's strategy in this case?

We define the critical level of the weather index, WI_{C}, as the level for which the payout is equal to the premium. If one would know in advance with certainty that $WI_{\mathrm{A}} < WI_{\mathrm{C}}$, it is profitable to buy in advance the insurance policy for the coming season. On the contrary, if $WI_{\mathrm{A}} > WI_{\mathrm{C}}$, it would be profitable not to buy the policy.

WI_{C} can be defined from the equation

$$PO(WI_{\mathrm{C}}) = P. \tag{17}$$

Substituting Eq. (11) into Eq. (17), we get

$$WI_{\mathrm{C}} = \frac{2S \cdot WI_{\max} - S^2 - WI_{\min}^2}{2(WI_{\max} - WI_{\min})}. \tag{18}$$

Under this critical level-based strategy, the farmer's income would be

$$I_t = \begin{cases} y(WI_{\mathrm{A},t}) + PO(WI_{\mathrm{A},t}) - P, & \text{if} \quad WI_{\mathrm{A},t} < WI_{\mathrm{C}}, \\ y(WI_{\mathrm{A},t}), & \text{if} \quad WI_{\mathrm{A},t} > WI_{\mathrm{C}}, \end{cases} \tag{19}$$

and the farmer's cumulated income would grow as defined by Eq. (15), where Eq. (19) is substituted.

'Imperfect forecast' case. In real world, no forecast is perfect. So we assume that the farmer is making their decision regarding the insurance policy on the basis of the forecasted value of the weather index. On the contrary, the farmer's actual income will depend on the actual value of the weather index that, in general, will deviate from its forecasted value:

$$I_t = \begin{cases} y(WI_{\mathrm{A},t}) + PO(WI_{\mathrm{A},t}) - P, & \text{if} \quad WI_{\mathrm{F},t} < WI_{\mathrm{C}}, \\ y(WI_{\mathrm{A},t}), & \text{if} \quad WI_{\mathrm{F},t} > WI_{\mathrm{C}}. \end{cases} \tag{20}$$

Specifically, we assume that the relation of the forecasted value to the actual value is given by the statistical model (12).

As before, the farmer's cumulated income will grow as defined by Eq. (15), where Eq. (20) is now substituted.

The dynamics of individual farmer's income under three alternative strategies defined in the present section are shown in Fig. 2 (green line: 'no forecast' case; blue line: 'perfect forecast' case; red line: 'imperfect forecast' case), while the dynamics of cumulated income are shown in Fig. 3 (with the same color scheme). Simulations shown in Figs. 2-3 correspond to the same realizations of the dynamics of actual and forecasted weather index as shown in Fig. 1. Note that for the chosen values of model parameters the 'no forecast' strategy often outperforms the 'imperfect forecast' strategy; consequently, in general, the cumulated income is higher for the 'no forecast' strategy than for the 'imperfect forecast' strategy. To summarize, in this case a strategy based on the forecast with rather low skill turns to be visibly suboptimal.

5 Model of the demand dynamics

Finally, we develop a simple model of the dynamics of the demand for weather index-based insurance policies. We assume that it might be dependent on the skill of the forecast of the weather index.

'Perfect forecast' scenario. In this case, we will simply assume that the growth rate of the number of insured is constant and is equal to r:

$$\frac{dN}{dt} = rN. \tag{21}$$

Obviously, this would yield the exponential growth of the number of insured,

$$N(t) = N_0 \exp(rt), \tag{22}$$

that would be a very optimistic scenario for the insurance industry.

'Imperfect forecast' scenario. In this case, our assumption is that the growth rate is modulated by a factor dependent on whether the forecasted value of the weather index was related to its critical value WI_{C} in the same way as the actual value:

$$\frac{dN}{dt} = \mathrm{sgn}(WI_{\mathrm{A},t} - WI_{\mathrm{C},t})\mathrm{sgn}(WI_{\mathrm{F},t} - WI_{\mathrm{C},t})rN, \tag{23}$$

where $\mathrm{sgn}(x)$ is a sign function equal to 1 if $x > 0$ and to -1 if $x < 0$. In the 'perfect forecast' case, the model (23) is reduced to the previous exponential model (21). However, in the 'imperfect forecast' case, the solution of Eq. (23) is a random process that might look very differently from exponential growth (and much less optimistic for the insurance industry, see Fig. 4 for a numerical example).

6 Conclusions and outlook

The presented study is focussed on modelling the strategies of farmers in a drought-prone region regarding the weather index-based insurance policy purchase, and also on simulating the dynamics of aggregate demand for this kind of insurance. Different strategies of individual farmers were explored, dependent on availability of the weather index forecast and on its skill. The economic analysis performed suggests that the skill of the forecast would affect the optimal strategy to be selected by a rational insurance policy buyer under conditions of inevitable uncertainty.

Our findings are based on a simple conceptual model. In particular, a simple power law was chosen to parameterize the dependence of crop yield on the weather index. Also, the dynamics of both actual and forecasted weather index was, somewhat arbitrarily, represented by a very simple random process. Bringing more realism to the model, in particular, adopting the crop yield parametrisations from real-world field data, and deriving actual/ forecasted weather indices from observations/ forecasts of weather and climate variables, is planned for future research. Implementation of this program would make the proposed generic modelling scheme crop- and region- specific, which, as mentioned above, is a necessary prerequisite for successful real-world implementation of weather index-based insurance projects.

In a simple weather index-based insurance model discussed in the present paper, the stochastic dynamics of actual weather index were simulated with a stationary random process. By generalizing this modelling scheme to the case of non-stationary random processes, it would be possible to consider weather indices with statistically significant trends that would be important for taking climate change effects into consideration. This would also likely shift the prospects for applications of this modelling scheme from the domain of weather services to the rapidly developing area of climate services. The generalization of the proposed model to include climatic trends is also left for further research.

Acknowledgments

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FIGURES

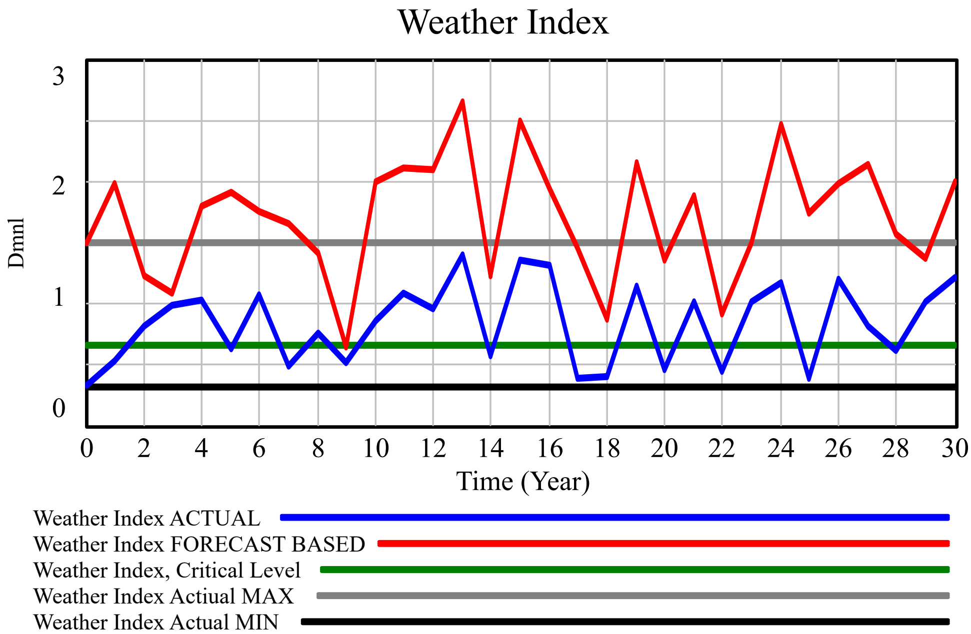

Figure 1: The dynamics of actual weather index (blue line) defined by Eq. (1) as an uncorrelated random process with uniform distribution (its upper and lower bounds are depicted by horizontal light-grey and dark-grey line, respectively). The forecast weather index (red line) is related to the actual weather index through a statistical model (12) with a constant systematic error and an uncorrelated random error. The critical level of the weather index (depicted by the horizontal green line) is defined by Eq. (17)

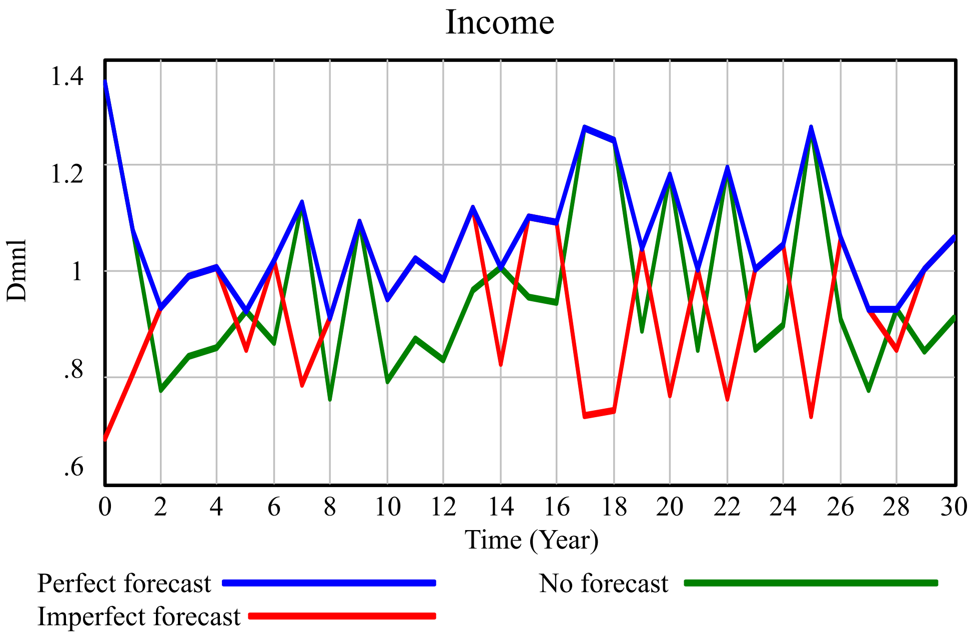

Figure 2: The dynamics of individual farmer's income under three alternative strategies defined in Sec. 4 (green line: 'no forecast' case; blue line: 'perfect forecast' case; red line: 'imperfect forecast' case) simulated for the same realizations of the dynamics of actual and forecasted weather index as shown in Fig. 1. Note that for the chosen values of model parameters the 'no forecast' strategy often outperforms the 'imperfect forecast' strategy

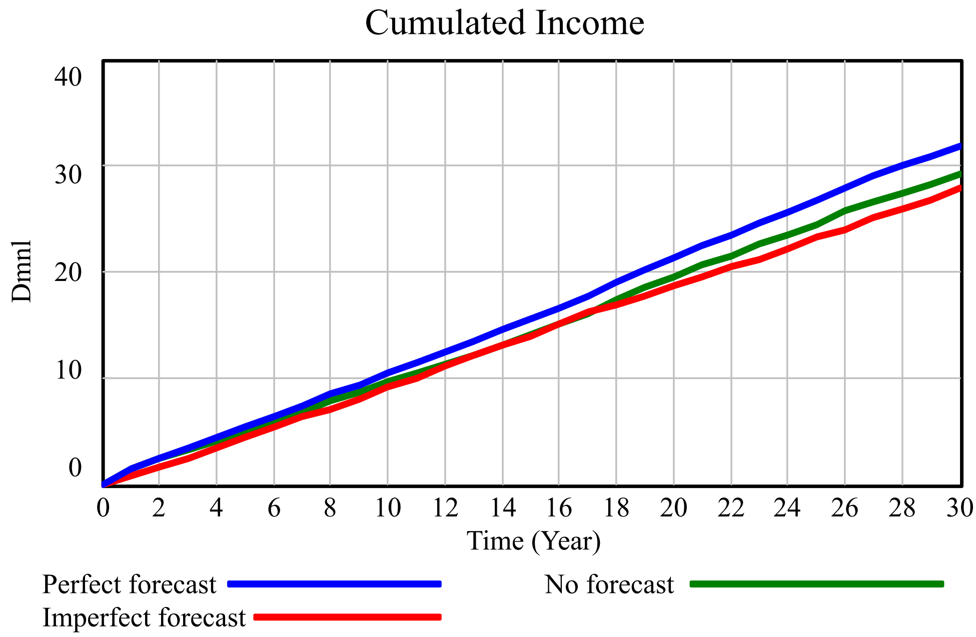

Figure 3: The dynamics of individual farmer's cumulated income under three alternative strategies defined in Sec. 4 (green line: 'no forecast' case; blue line: 'perfect forecast' case; red line: 'imperfect forecast' case) simulated for the same realizations of the dynamics of actual and forecast weather index as shown in Fig. 1. Note that, in general, the cumulated income is higher for the 'no forecast' strategy than for the 'imperfect forecast' strategy (for the chosen values of model parameters)

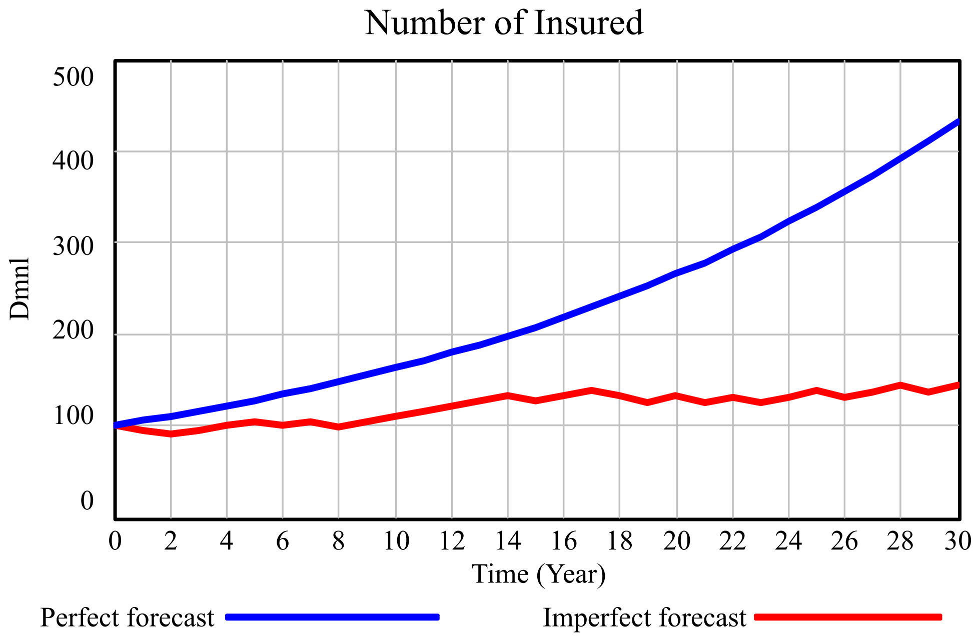

Figure 4: The dynamics of the number of insured (blue line: the ‘perfect forecast’ case; red line: the ‘imperfect forecast’ case). See Sec. 5 for the details