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Technology forecasting using time series intervention based trend impact analysis for wheat yield scenario in India

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ABSTRACT

In conventional Trend Impact Analysis (TIA), a baseline model based forecast is generated using historical data. Also, a set of future events and their impacts are identified utilizing prior knowledge. Further, these impacts and events are combined with baseline to generate possible future scenarios through simulation. One of the main drawback of this approach is that it cannot deal with unprecedented future technologies or rare events. Further, it cannot answer about expected future, if some specific event occurs at a particular period in future. Intervention analysis has been traditionally used to assess the impact of any unprecedented event occurring at known times on any time series. It consists of a single impact parameter and a slope parameter for a particular event. Hence, a new TIA method has been developed by combining conventional TIA with the intervention model instead of simulation, The traditional interventional model were modified as per the requirement of TIA to incorporate three impact parameters for any number of events. For the unprecedented future event, impact of the event is known while time at which event will occur is not known in advance. A formula for estimating slope parameter has been derived. The proposed TIA approach is capable to handle the influence of any unusual occurrences on the structure of the fitted model while providing forecasts of future values. The data requirements in this proposed new TIA is less as compared to conventional TIA approach. It can also answer about expected future if some particular event occur in particular time. The proposed TIA approach has been empirically illustrated for wheat yield scenario at All-India level. For this, three events each with three degrees of severity have been considered. All possible scenarios were generated from which preferable futures can be chosen.

1. Introduction

Forecasting in a systematic and scientific way can play a crucial role for providing timely information to policy makers on food shortages and/or surpluses for timely management of food supplies. This is more important in case of adverse environmental conditions.

Wheat is the second most important food-grain crop after rice in India. It is the staple food of millions of Indians. Therefore, not only forecasting of wheat yield but also technology forecasting related to this crop is very important for policy makers of the country. The applications of quantitative technique i.e. statistical model particularly ARIMA model were used extensively for forecasting crop are, yields or production data have been reported for pigeon pea production (Sarika et al., 2011), sugarcane area, production and productivity (Suresh and Priya, 2011), maize area and production (Badmus and Ariyo, 2011), rice area and production (Prabakaran and Sivapragasam, 2014) etc. The approach of employing ARIMA modeling for forecasting provides better result for short period but for longer period this approach may not produce a reliable forecast as it does not consider the effects of unprecedented future events or technologies that could cause deviation from the model.

The domain of technology forecasting not only incorporates, the benefits of quantitative approaches but also takes care of unprecedented future events. Therefore, efforts are often made to fuse qualitative approaches with them to better predict the future values. One such important hybrid forecasting approach is the Trend Impact Analysis (TIA) (Gordon, 2003; Glenn, 2003; Firat et al., 2008). TIA consists of two steps. In the first step, a baseline forecast is generated using a suitable statistical model based on historical data. In the second step, a set of future events and their impacts are identified utilizing prior knowledge which are elicited/validated from/by experts or by collecting information employing qualitative forecasting approaches like Environmental Scanning, Delphi Survey etc. This is further followed by application of Monte Carlo simulation in the TIA algorithm which combines the impact and event probability judgments with the outcomes of the baseline

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scenario (model based forecasts) to generate a fan of possible future scenarios. Based on these scenarios, the median, 5th and 95th percentile scenarios are computed thus specifying three divergent scenarios.

There are several instances of application of TIA in industry and other divergent domains like aviation, energy, transportation etc. (Gordon, 2003; Winkless, 2004). TIA approach has been applied in the field of agriculture as well, for predicting future fruit consumption of Netherland (Hennen and Benninga, 2009) and for projections of Eucalyptus cultivation in Brazil (Lotfi and Pela, 2009).

There are instances of modifying the TIA approach. An enhanced TIA approach by considering three degrees of severity; low, medium and high was developed for each unprecedented future event to generate fan of possible future scenarios (Agami et al., 2008). Attention was paid to surprise-free forecast aspects of TIA by employing neural network based approach for forecasting the base-line scenario to enhance the prediction ability of TIA (Agami et al., 2009). Further, an advanced mechanism was proposed to generate more valid estimates to the probability of occurrence of an unprecedented event as a function of time with divergent degrees of severity employing fuzzy logic (Agami et al., 2010).

The intervention modeling and analysis are used for adjustments of impact of any unprecedented events in the time series data. First applications of intervention model was done to study impact of air pollution controls, economic controls on the consumer price index (Box and Tiao, 1975). A good account on intervention modeling is given in Box et al. (1994), Madsen (2008), Yaffee and McGee (2000) etc. Intervention model was also applied to study impact of interventions in an experimental design (Krishnamurthi et al., 1989), to quantify the impact of sales promotional data (Shao, 1997), to improve methods for forecasting in telemarketing centers (Bianchi et al., 1998), to analyze the epidemiological situation in England and Wales for the period of 1940–1990 (Girard, 2000), to evaluate the policies (Mcleod and Vingilis, 2005), to forecast five star hotels' occupancy (Ismail et al., 2009), to measure the business process reengineering (Lam et al., 2009), to study survey redesign (Brakel and Roels, 2010) and for modeling and forecasting cotton yield of India considering the introduction of Bt cotton as unprecedented technology (Ray et al., 2014).

In this study, new TIA approach has been proposed and it was used for predicting Wheat yield scenario for India. As crop yield of a future year shall depend on future unprecedented technologies (say, new variety and other inputs such as nano-chemicals and fertilizers, new cultivation procedure, better management practice etc.) and rare events (say, extreme weather conditions like drought, flood, high temperature, water logging, etc.) which are unprecedented events. Apart from this, other events could also be introduced/occurs such as new environmental regulations, economic policy changes, employee strikes, bomb blasts, special promotion campaigns, natural disasters etc. In all these cases, there is a strong need for further modification of existing or modified TIA approach (Hennen and Benninga, 2009; Lotfi and Pela, 2009; Agami et al., 2008, 2009, 2010). Therefore, in this proposed methodology, an intervention analysis based time series model has been used to generate all-possible scenarios instead of Monte Carlo simulations when future events are considered as introduction of new technologies or occurrence of rare events.

With this intervention analysis, the proposed TIA approach is capable to handle the influence of any unusual occurrences on the structure of the fitted model and adjusts for estimates of model parameters through adopting such patterns while providing forecasts of future values. Further, in this study, the conventional intervention model has been modified to accommodate the parameters of TIA. Also, this newly proposed TIA techniques has been used in the analysis of Wheat yield in India under different unprecedented events.

The rest of the paper is organized in different sections. In Section 2, a brief overview of intervention model is given. In Section 3, modified intervention model has been explained. Then Section 4, the proposed methodology for TIA has been explained in detail. Finally, in Section 5, the proposed approach has been empirically illustrated for various wheat yield scenarios at All-India level considering three situations: two unprecedented future wheat variety breeding technologies (heat tolerant and rust resistant) and occurrence of one rare event (increase in temperature) followed by conclusions in Section 6.

2. Intervention model

The conventional intervention model can be represented as follows:

$$Y_t = \frac{\omega(B)}{1-\delta(B)} B^b I_t + N_t \tag{1}$$

where, Y_t is the dependent (time series) variable, I_t is the indicator variable coded according to the type of intervention, $\delta(B) = 1 + \delta_1 B + \ldots + \delta_r B^r$ i.e. slope parameter, $\omega(B) = \omega_0 + \omega_1 B + \ldots + \omega_s B^s$ i.e. impact parameter, b is delay parameter; B represents Backshift operator i.e. $B^a Y_t = Y_{t-a}$, N_t is the noise series, which represents the background observed series Y_t but without intervention effects i.e. N_t is nothing but the ARIMA model. The parameters of Intervention model is represented graphically in Fig. 1.

In general, the values an intervention variable can depends on types of interventions such as pulse (one time occurrence), ramp, step etc. In this study, only step intervention is used which is given by

$$S_t = \begin{cases} 0 & t < T' \\ 1 & t \geq T' \end{cases}$$

With T' is the time at which intervention has occurred and S_t represents the indicator variable for such intervention. Divergent response patterns are possible through different choices of intervention components. Different intervention components with their output responses are given in (p. 464 Box et al., 1994).

Intervention analysis has been traditionally used to assess the impact of any unprecedented event occurring at a known point of time (i.e. already occurred event in a recent time period but not in a future time period) on any time series of interest. On the other hand, in TIA, it is assumed that for the unprecedented event (or set of events) that will occur in future, the estimated impact(s) of the event (or set of events) are elicited/validated from/ by experts. Another issue in TIA is that, the time point at which event will occur is also not known in advance. Hence, the parameter which has to be estimated in intervention analysis is known in TIA, but the time point is unknown. Therefore, by varying the time points, generation of different scenarios is possible through this analysis.

3. Modified intervention model for new TIA approach

In traditional TIA algorithm, it is assumed that when any unprecedented event occurs, it will have some initial impact and after some time, the impact will be maximum (maximum impact) and finally, after a time period, the impact will be constant (Steady-State impact). Moreover, there are two time parameters in TIA viz., time to maximum impact and time to steady-state impact respectively. The parameters of TIA is represented graphically Fig. 2 (Agami et al., 2008).

It may be noted that instead of a single event and single impact parameter as is the case with traditional intervention modeling, TIA has three impact parameters viz., initial impact, maximum impact and steady-state impact for each event. Let the TIA parameters be defined as follows:

ω_0 = initial impact
ω_m = maximum impact
ω_s = steady-state impact
t_m = time to maximum impact
t_s = time to steady state impact
n = number of events
k = degree of severity

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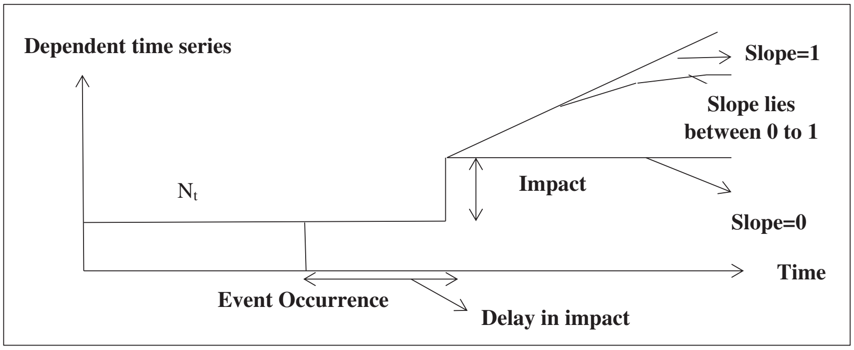

Fig. 1. Parameters in Intervention model.

Now, from initial impact up till one time point before the maximum impact time point i.e. (1, 2…t_m-1), the form of the intervention component will be: $\frac{\omega_0}{1-\delta_0(B)}$ $0\le\delta_0\le1$. Again, from maximum impact point up till one time point before the steady impact time point i.e. (t_m,t_m+1, …,t_s-1), the form of the intervention component will be: $\frac{\omega_m}{1-\delta_m(B)}$ $-1\le\delta_m\le0$. Again, from steady impact time point to the end of forecast horizon the form of the intervention component will be:ω_s. From the standpoint of initial time, maximum impact occurs after a delay of (t_m-1) and steady-state impact occurs after a delay of t_s-1 time points. Hence, by inclusion of these three intervention components along with the step intervention variable S_t appropriately lagged by using backshift operator depending upon the delay with which it occurs, the intervention model (1) can be accordingly written as proposed intervention based TIA model in Eq. (2).

$$\hat{Y}_t = \frac{\omega_0}{1-\delta_0(B)} S_t + \frac{\omega_m}{1-\delta_m(B)} B^{t_m-1} S_t + \omega_s B^{t_s-1} S_t + N_t \tag{2}$$

It can be seen that the conventional intervention model (Eq. (1)) consists of only a single impact parameter and a slope parameter for a particular/single event. Slope parameter is required for varying the level of impact parameters over time. However, the proposed intervention model has been modified to incorporate three impact parameters for any number of events. In this proposed TIA, impact parameters needs to be estimated by some qualitative approach. However, the slope parameter of this proposed model needs to be estimated.

Having the initial impact as ω_0, the subsequent impact parameters are ω_1,ω_2, ω_3, …, ω_{t_m}after 1,2,3…, t_m-1 time periods of intervention or event occurrence. Then

$$\omega_1 = \omega_0 + \omega_0\delta_0$$

$$\omega_2 = \omega_0 + \omega_1\delta_0 = \omega_0 + \omega_0\delta_0 + \omega_0{\delta_0}^2$$

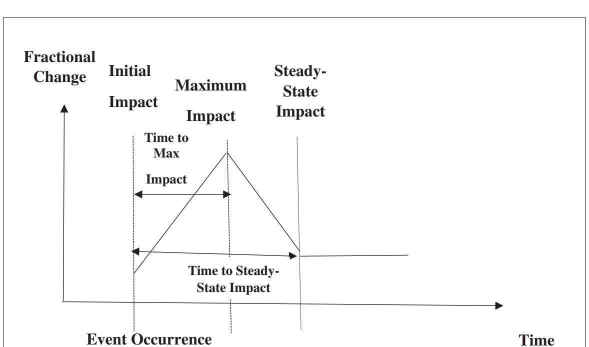

Fig. 2. Parameters in TIA.

Proceeding on similar lines,

$$\omega_m = \omega_0 + \omega_0\delta_0 + \omega_0{\delta_0}^2 + \omega_0{\delta_0}^3 + \ldots + \omega_0{\delta_0}^{t_m}$$

$$\frac{\omega_m}{\omega_0} = 1 + \delta_0 + {\delta_0}^2 + {\delta_0}^3 + \ldots + {\delta_0}^{t_m}$$

Taking logarithms on both sides and on simplification,

$$\delta_0 = \exp\left(\frac{2}{t_m * (t_m+1)} * \log\left(\frac{\omega_m}{\omega_0}\right)\right) \tag{3}$$

Similarly,

$$\delta_m = -\exp\left(\frac{2}{t_s * (t_s+1)} * \log\left(\frac{\omega_s}{\omega_m}\right)\right) \tag{4}$$

Now extending the equation for n number of events and k degrees of severity, the model (2) can be written as

$$\hat{Y}_t = \sum_{i=1}^{n}\sum_{j=1}^{k} \frac{\omega_{0ij}(B)}{1-\delta_{0ij}(B)} S_t + \sum_{i=1}^{n}\sum_{j=1}^{k} \frac{\omega_{mij}(B)}{1-\delta_{mij}(B)} B^{(t_{mi}-1)} S_t + \sum_{i=1}^{n}\sum_{j=1}^{k} \omega_{sij}(B) B^{(t_{si}-1)} S_t + N_t \tag{5}$$

where, N_t is nothing but the base forecasting which can be obtained by employing suitable statistical model such as ARIMA. Eq. (5) is the modified intervention model by utilizing this model for a given number of n events with degree of severity and impact parameters all-possible scenarios can be generated.

4. Proposed new TIA approach

The proposed TIA approach used the modified intervention model discussed above in Section 3 to generate all possible scenarios based on unprecedented events. The data requirements in this proposed new TIA is less as compared to conventional TIA approach. It can also answer about expected future if some particular event occur in particular time. The newly proposed TIA approach is based on three major steps i.e. (i) to get baseline forecast may be using ARIMA model, (ii) to use modified intervention model (proposed in Section 3) for generation of all possible scenarios and (iii) integration of baseline forecast with the modified intervention model.

In the existing approaches of TIA (Hennen and Benninga, 2009; Lotfi and Pela, 2009; Agami et al., 2008, 2009, 2010) require subjective probability associated with each event for implementation of Monte Carlo simulation approach. As the proposed algorithm, assumed that unprecedented event/technology (or set of events/technologies) can occur any time in future, hence, the proposed

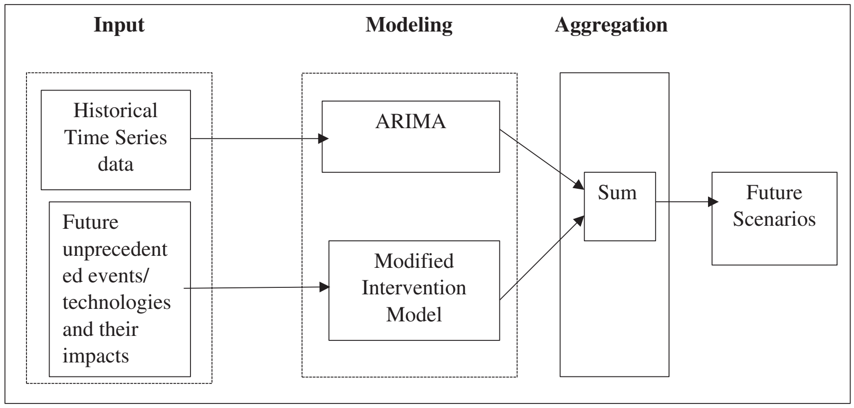

Fig. 3. Proposed TIA approach.

algorithm does not require subjective probabilities of events. In addition, the existing TIA approaches require huge amount of data. For example, suppose an event occurs at time t, then it is required to obtain impact at time t, t + 1, t + 2, …,t_m, t_{m+1}, …t_{s-1},t_s. However, in this proposed approach, for each particular event five parameters need to be specified i.e. initial impact, maximum impact, steady-state impact, time to maximum impact and time to steady-state impact.

4.1. Base-line forecast

Baseline forecasts are obtained by utilizing historical data which are time series data. Let, ARIMA model was utilized to generate base-line forecasts. An ARIMA model is given by

$$\phi(B)(1-B)^d y_t = \theta(B)\varepsilon_t \tag{6}$$

where

$\phi(B) = 1-\phi_1 B-\phi_2 B^2-\cdots-\phi_p B^p$ (Autoregressive parameter)

$\theta(B) = 1-\theta_1 B-\theta_2 B^2-\cdots-\theta_q B^q$ (Moving average parameter)

ε_t = white noise or error term
d = differencing term
B = Backshift operator i.e. $B^a Y_t = Y_{t-a}$

ARIMA methodology is carried out in three stages, viz. Identification, estimation and diagnostic checking. Parameters of ARIMA model are tentatively selected at the identification stage and at the estimation stage parameters are estimated using iterative least square techniques. The adequacy of the selected model is then tested at the diagnostic checking stage. If the model is found to be inadequate, the three stages are repeated until satisfactory ARIMA model is selected for the time-series under consideration.

4.2. Generation of scenarios

In this proposed TIA methodology, generation of a binary matrix for all possible situations which are combinations of occurrence/ non-occurrence of events can be obtained. For n events, a total of $(2^n - 1)$ situations occur for a fixed time point (i.e. year). For each time point, utilizing the modified intervention Eq. (5), generation of all possible future scenarios can be obtained. Thus, for forecast horizon h, with k number of degrees of severity within each of n events can be considered. In this case, a total of $[h_* k_* (2^n - 1)]$ scenarios will be generated. For example, considering three events, $2^3 - 1 = 7$ situations will occur which are given below as a binary matrix:

Event situation	E1	E2	E3
1	1	0	0
2	0	1	0
3	0	0	1
4	1	1	0
5	0	1	1
6	1	0	1
7	1	1	1

Note: 1: event occurred; 0: event did not occurred.

The integration of baseline forecast with modified intervention model in proposed TIA approach can be graphically represented as below (Fig. 3).

In this case ARIMA model can be fitted employing SAS-ETS ver 9.4 (http://www.sas.com/en_us/software/sas9.html) or any other relevant software. However, a SAS Macro was developed (http://support.sas.com/documentation/cdl/en/mcrolref/61885/HTML/default/viewer.htm#macro-stmt.htm) for generation of scenarios. The main advantage of the proposed TIA approach is to generate all possible scenarios and identify expected scenario, if some particular event occurred at particular time. In addition, the data requirements in case of proposed TIA method are less as compared to existing approach.

Table 1
The apriori percentages of various impacts of events and time to reach such impacts.

Event	Initial impact (in %)	Maximum impact (in %)	Steady state impact (in %)	Time to maximum impact (Year)	Time to steady state impact (Year)
E1 (L)	5	20	15	7	15
E1 (M)	10	25	20	7	15
E1(H)	12	30	25	7	15
E2 (L)	2	10	6	8	12
E2 (M)	3	12	8	8	12
E2(H)	4	14	10	8	12
E3 (L)	1	5	2	10	15
E3(M)	3	10	8	10	15
E3(H)	4	15	12	10	15

Here,
E1 = heat tolerant wheat variety breeding technology.
E2 = rust resistant wheat variety breeding technology.
E3 = increase in temperature (event).
L = low degree of severity, M = medium degree of severity,
H = High degree of severity.

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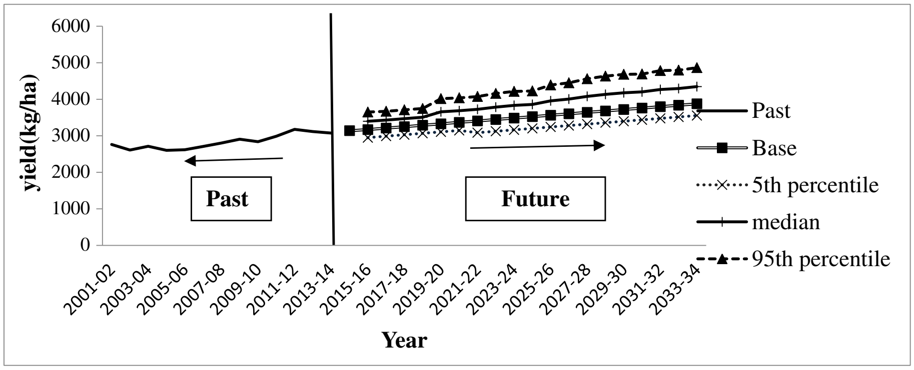

Fig. 4. scenarios generated **Note:** As in 2014–15, no such event occurred so there is only base-line forecast for that year.

5. Numerical illustration

The proposed approach has been empirically illustrated for Wheat yield scenario at All-India level. For this, three pre-specified events/ technology impacts have been considered, as if they were said to occur in future in the long run. The events are heat tolerant Wheat variety breeding technology, rust resistant Wheat variety breeding technology and increase in temperature (event). In these, first two will have positive impacts, the third will have a negative impact. Three degrees of severity for each unprecedented event were also been considered. Time series data of All-India Wheat yield during 1951–52 to 2013–14 were considered to envision the long term future i.e. 20 years henceforth. For generating baseline forecasts, ARIMA model was utilized. This model was utilized to generate subsequent forecasts 20 years ahead.

Data during the period 1951–52 to 2003–04 was utilized for model fitting purpose and data during the period 2004–05 to 2013–14 was utilized for model validation. Firstly, ARIMA model was fitted. The best fitted model was ARIMA (1, 1, 0) given by

$$y'_t = 38.90 - 0.38 y'_{t-1} + \varepsilon_t \tag{7}$$

where $y'_t = y_t - y_{t-1}$.

The apriori percentages of various impacts of events and time to reach such impacts were constructed using guess estimates/ experts' knowledge which are given below in Table 1.

Now, deploying the proposed approach for 20 years forecast horizon by interspersing impact of three events each of which having three degrees of severity, a total $20 * 3 * (2^3 - 1) = 420$ divergent scenarios were generated. Let us assumed in 2014–15, no such event occurred, 420 scenarios was reduced to $420 - [1 * 3 * (2^3 - 1)] = 399$ scenarios excluding base forecast. Further, 5th percentile, 95th percentile and median were computed from these scenarios to give three divergent futures (Fig. 4).

Thus this approach can also answer as to what will be the expected scenario, if some particular event occurred at any particular time. For instance, suppose heat tolerant wheat variety breeding technology is introduced in the year 2024–25 with medium degree of severity, then the expected scenario will be as given below (Fig. 5):

Similarly scenario for other particular situation can also be generated.

6. Conclusions

A new TIA approach based on time series intervention model has been developed. In order to develop this, the conventional intervention model has been modified to accommodate the TIA parameters. This approach is suitable when the future events are considered as introduction of new technology or rare events. The major advantage of this proposed TIA approach is that (i)it can generate all possible scenarios, (ii) can be easily modified to answer about expected future if some particular event occur in particular time. The study reveals the advantages of proposed TIA methodology over the existing crop yield forecasting approach is in terms of its greater utility by providing scenarios for a broader forecast horizon. A possible future work will be to extend the theory of intervention analysis for any kind of events because it has the potentiality to generate all possible scenarios without repetition.

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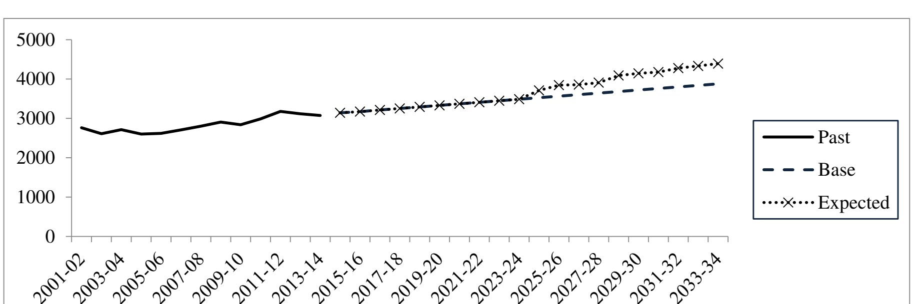

Fig. 5. scenario for heat tolerant wheat variety breeding technology is introduced in the year 2024–25 with medium degree of severity.

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