Crop Monitoring as an
E-agricultural tool in
Developing Countries

ASSESSMENT REPORT ON MULTI-MODEL APPROACH FOR RICE MONITORING

Reference: ***E-AGRI_D33.2_Report on the assessment of multi-model approach for rice monitoring***

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Version: 1.0

Date: 21/11/2013

DOCUMENT CONTROL

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Release	Date	Pages	Description	Editor(s)/Reviewer(s)
1.0	24/11/2013	31	D33.2 - Report	

TABLE OF CONTENT

LIST OF FIGURES

EXECUTIVE SUMMARY

The BioMA models WARM, CropSyst and WOFOST were parameterized for rice in Jiangsu within E-AGRI WP3 tasks already completed and reported (D32.3, D32.4), and the BioMA platform for rice monitoring was successfully evaluated and reported in Month 33 (D33.1).

This document reports on the evaluation of the BioMA platform for multi-model rice monitoring. The rationale behind this approach refers to the possibility that:

(i) the different approaches implemented in different crop models to formalize biophysical processes involved with crop growth and development could make a model more suitable than others under certain conditions; and that

(ii) while changing conditions, a different model could become the most suitable, since conditions are changed.

The results achieved in this study fully demonstrate the above concepts: WARM resulted the most suitable for rice yield forecasting in Jiangsu when the forecasting event is triggered at the end of the season (physiological maturity is reached in all the simulation units), whereas WOFOST provided more reliable forecasts in earlier stages (four decades before maturity).

These results are coherent with recent tendencies within the international modellers community (AgMIP), increasingly targeting multi-model approaches to crop and cropping system simulations.

According to the authors, this is the first time a multi-model approach for in-season monitoring and forecasting activities was developed and tested.

1. Introduction

Multi-model approaches to crop growth and development are increasingly discussed within the modellers community, and international projects and networks aimed at coordinating scientists from different modelling schools are active since some years ago (e.g., AgMIP, The Agricultural Model Intercomparison and Improvement Project; http://www.agmip.org/).

Most of these initiatives are evaluating the possibility of using multi-model systems for deriving synthetic outputs from statistics calculated on the outputs of the single models. As an example, Asseng et al. (2013) demonstrated – using 27 different crop models and datasets coming from four different countries – that wheat yield estimates can be estimated with a higher reliability by using the median of the outputs form different models.

In this case, we tested the hypotheses that different models could be more suitable than others under certain conditions, and that the "most suitable" model could be different while changing conditions (region, climate, management), or moment during the crop cycle when the forecasting event is triggered.

2. Materials and methods

2.1. Modelling solutions

The three BioMA models used in this study – WARM (Confalonieri et al., 2009), CropSyst (Stöckle et al., 2003) and WOFOST (Van Keulen and Wolf, 1986) – have been already presented and described in previous E-AGRI reports (e.g., D32.1). For all of them, modelling solutions including disease simulation were developed, using the approach proposed by Bregaglio et al. (2013) for infection and the UNIMI.Diseases component for disease progress. Since process-based approaches for the estimation of the interaction between plants and fungal pathogens require (i) hourly time step simulations and (ii) inputs normally not available in large area databases like those used for operational crop monitoring and yield forecasting services, a series of generator of weather data was coupled to the modelling solutions. In particular, the following software components implementing weather data generators were used:

- CRA.Clima.Wind for wind speed generation (Donatelli et al., 2009; http://agsys.cra-cin.it/tools/wind/help/);
- CRA.Clima.AirT for hourly air temperature data (Donatelli et al., 2010; http://agsys.cra-cin.it/tools/airtemperature/help/);
- CRA.Clima.Evapotranspiration for hourly air relative humidity data (Bregaglio et al., 2010; http://agsys.cra-cin.it/tools/evapotranspiration/help/);
- JRC.IPSC.MARS.Diseases.LeafWetness for leaf wetness data (Bregaglio et al., 2011; http://agsys.cra-cin.it/tools/leafwetness/help/).

Hourly weather data are generated at runtime, thus without needing extension of the database compared to what is normally used by CGMS-type applications.

2.2. Simulation experiments

2.2.1. Data and parameterizations

Rice was simulated on each of the elementary simulation units corresponding to the cells of the 25 km × 25 km grid of the European Centre for Medium-Range Weather Forecast (ECMWF) where rice is cultivated according to the rice crop mask shown in Figure 1.

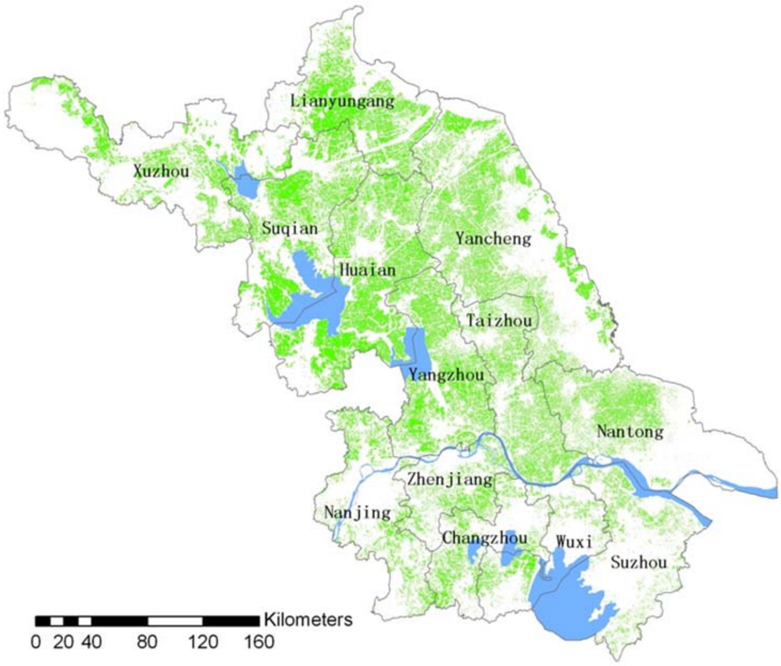

Figure 1 Crop mask of rice (green areas) in the Jiangsu province

According to the information provided by the local partners, simulations started in mid-may for all the test years, with the sowing date set to June 1.
Parameterizations for the crop models derives from the calibration and validation activities detailed in E-AGRI report D32.3. Parameters for the UNIMI.Disease model (referring to the fungus Magnaporthe oryzae B. Couch, agent of rice blast disease) where derived from the literature, since they are related to pathogen characteristics with a clear biological meaning and high quality measurements are available from experiments carried out in controlled environment.
Aggregation of simulated data at province level (based on percentage crop presence in simulation units) was performed using the same rice crop mask used to identify simulation units. A quadratic trend was always used for the forecasting activities.

2.2.2. Testing the multi-model approach

In order to test the multi-model approach to rice monitoring, the following factors were considered:
- moment when the forecasting event is triggered;
- climate conditions explored.

Concerning the forecasting moment, it was triggered three times: (i) when all the crops simulated in all the simulated spatial units have reached the physiological maturity, (ii) two decades before, and (iii) four decades before.

This test was aimed at evaluating possible changes in relative model suitability – for yield forecasting purposes – while approaching the harvest period. This test should be considered particularly interesting, since it directly deals with the capability of the system to provide timely estimates of what the actual yield will be at the end of the season.

The exploration of different climate conditions is decidedly interesting too, since could lead to situations where different models are the most suitable for different regions. However, only official yield statistics at province level were available for this study. We thus tried to emulate the presence of different conditions by dividing the available historical series (1990-2009) in two sub-series partly overlapped, one from 1990 to 2001, and the other from 1998 to 2009. This was done considering that temperature in the second part of the series were higher than in the first. So, even without having the possibility here to test the forecasting capability of the multi-model approach in different regions (characterized by a different climate), we tested its capability in the same area but on time series differing for the climate conditions the crop was exposed to.

The resulting tests performed with each of the three models are summarize in Table 1, and led to 27 forecasting experiments, each deriving from 20-year simulations on 189 elementary simulation units.

Table 1 Factors considered during the study.

Test ID	Monitoring time	Time series
1	Physiological maturity reached in all simulation units	1990-2009
2		1990-2001
3		1998-2009
4	2 decades before physiological maturity is reached	1990-2009
5		1990-2001
6		1998-2009
7	4 decades before physiological maturity is reached	1990-2009
8		1990-2001
9		1998-2009

Simulation results were post-processed, together with historical series of statistical data, to produce the forecasts using the MARS CGMS Statistical Toolbox application integrated in the BioMA environment. Forecasts reliability for each of the combination crop model × monitoring time × climate conditions were evaluated by means of indices of agreement between official and forecasted yields resulting from a cross-validation (leave-one-out): R^2 (coefficient of determination of the linear regression) and RRMSE (relative root mean square error, expressed as percentage).

3. Results and discussion

Results are presented in the following three sections, referring each to a series of climate conditions explored: 1990-2009 (whole series) in section 3.1, 1990-2001 (first part of the series) in section 3.2, and 1998-2009 (second part of the series) in section 3.3.
For each section, the differences among the evaluated monitoring time are discussed.

3.1. Time series 1990-2009

Results of the multi-model approach to rice monitoring achieved using the whole time series are shown in Table 2 and in Figures 2, 3 and 4.
The cross validation performed by using the data from the whole available time series (1990-2009) indicated WARM as the most reliable model when the forecasting event is triggered at harvest time (RRMSE = 2.23%), followed by CropSyst and WOFOST (RRMSE 2.78% and 2.94%, respectively).
When moving the forecasting event two decades before, WARM remains the model with the highest accuracy, although the ranking of WOFOST and CropSyst changed, with CropSyst presenting, in this case, the worst performances (RRMSE = 3.04%).
The model accuracy in case of the earliest forecasting event (four decades before physiological maturity) led – in general – to achieve a lower level of accuracy: the average R^2 is 0.77, whereas it was 0.82 for the late forecasting events. This is explained by the largest part of season not simulated by the models, and thus by the largest amount of total variance in official yields unexplained using process based techniques and left to the statistical post-processing. In this case, however, WOFOST achieved the best metrics (RRMSE = 2.78%), providing higher guarantees in case of early monitoring activities and overcoming WARM (RRMSE = 2.86%).

Table 2 Multi-model rice monitoring in Jiangsu; results of the cross validation using the time series 1990-2009.

Decades before maturity is reached in all the simulation units	WARM	WOFOST	CropSyst
	R^2		
0	**0.87**	0.78	0.80
2	**0.89**	0.80	0.76
4	0.79	**0.80**	0.72
	RRMSE (%)		
0	**2.23**	2.94	2.78
2	**2.06**	2.81	3.04
4	2.86	**2.78**	3.27

Figures 2, 3 and 4 show the agreement between official and forecasted yields.
In general, all the models were able to reproduce the inter-annual yield variability when the forecasting event was triggered at maturity (Figure 2), although none of them succeeded in forecasting the exceptional yields recorded in Jiangsu in 1998. WARM also overestimated official yields for the years 1997 and 2005, although the number of overestimated and underestimated yields for the other two models is higher. This is particularly true for WOFOST that, with the exception of the good performance in the markedly unfavourable 2003 season, appeared as the less able to capture anomalies, presenting the smoothest trend in forecasted yields.
This tendency of WOFOST can be observed also when the forecasting event is triggered two decades before maturity (Figure 3), with a marked underestimation for 1998 (also present in CropSyst results) and underestimation for 1994 and 2005. WARM confirmed the good performances already shown for the forecasting event at maturity, whereas CropSyst appeared as the model most penalized by the anticipation of the forecasting event.
Figure 4 shows the results for the earliest forecasting event. In this case, WOFOST predictions were those presenting the highest reliability, whereas both WARM and CropSyst decrease their accuracy. For WARM, this is explained by a slightly larger uncertainty affecting the whole series; for CropSyst, the main reason is related to marked under- or overestimations in years where yields strongly deviated from the quadratic trend.

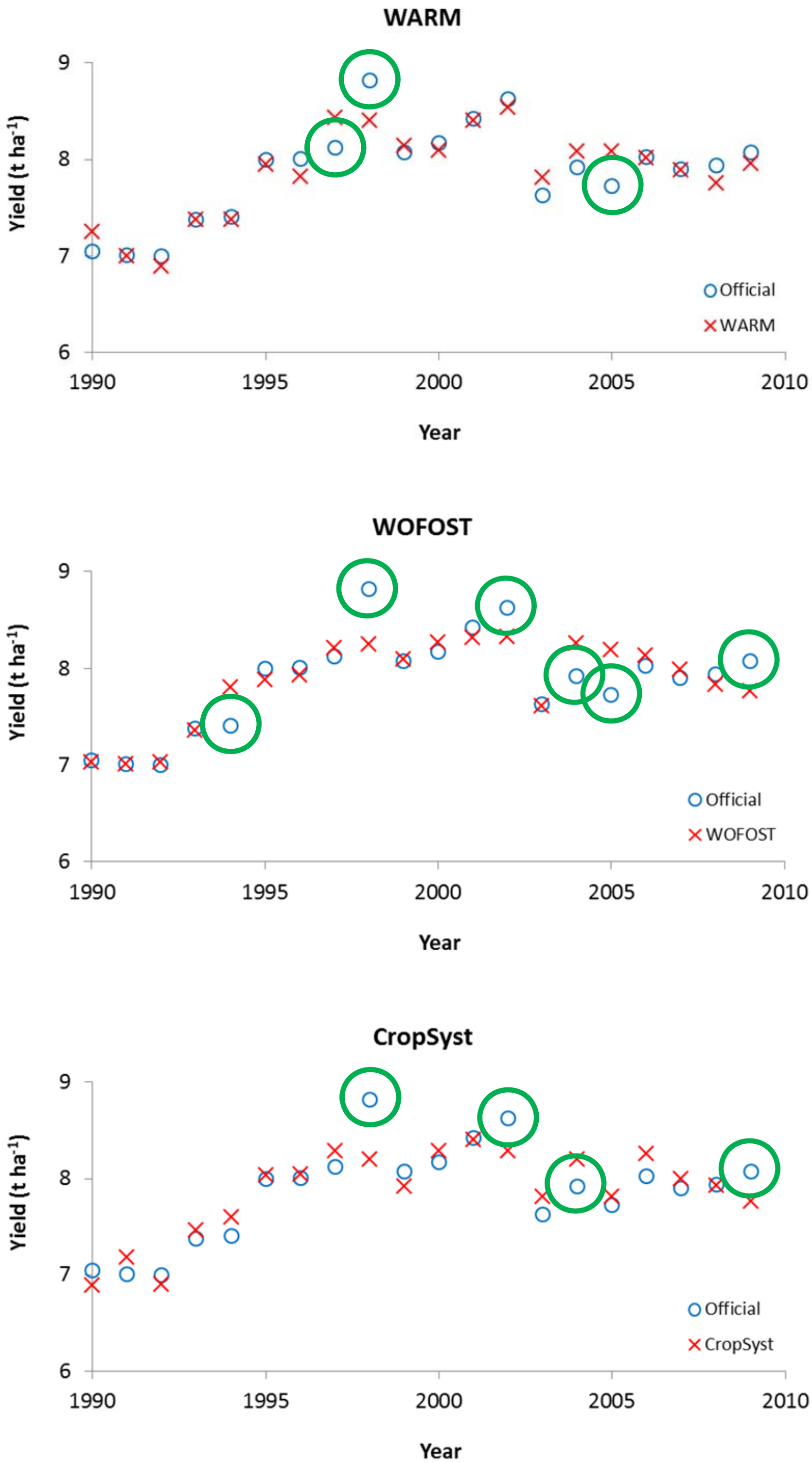

Figure 2 Multi-model monitoring; 1990-2009; maturity decade.

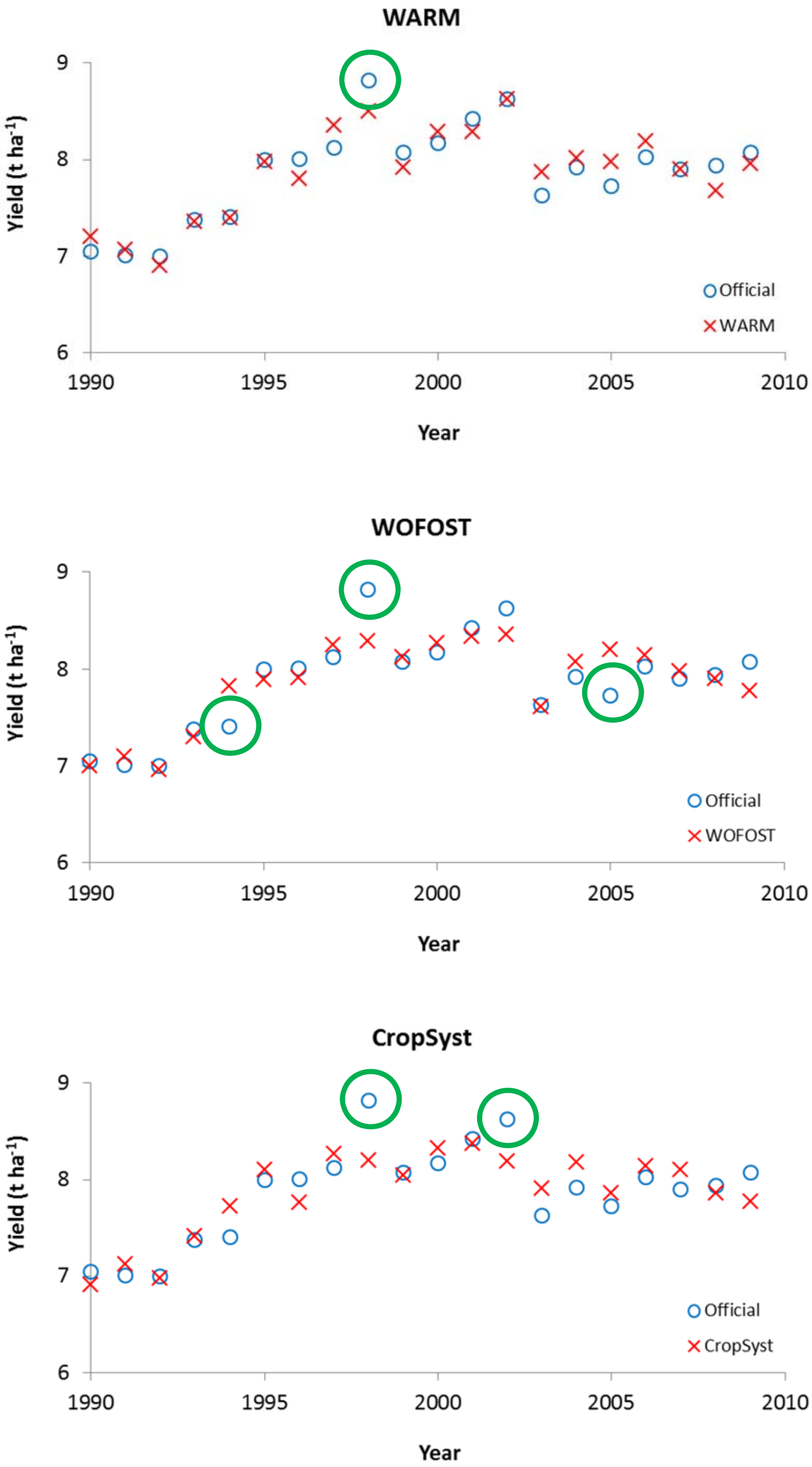

Figure 3 Multi-model monitoring; 1990-2009; decade: maturity -2.

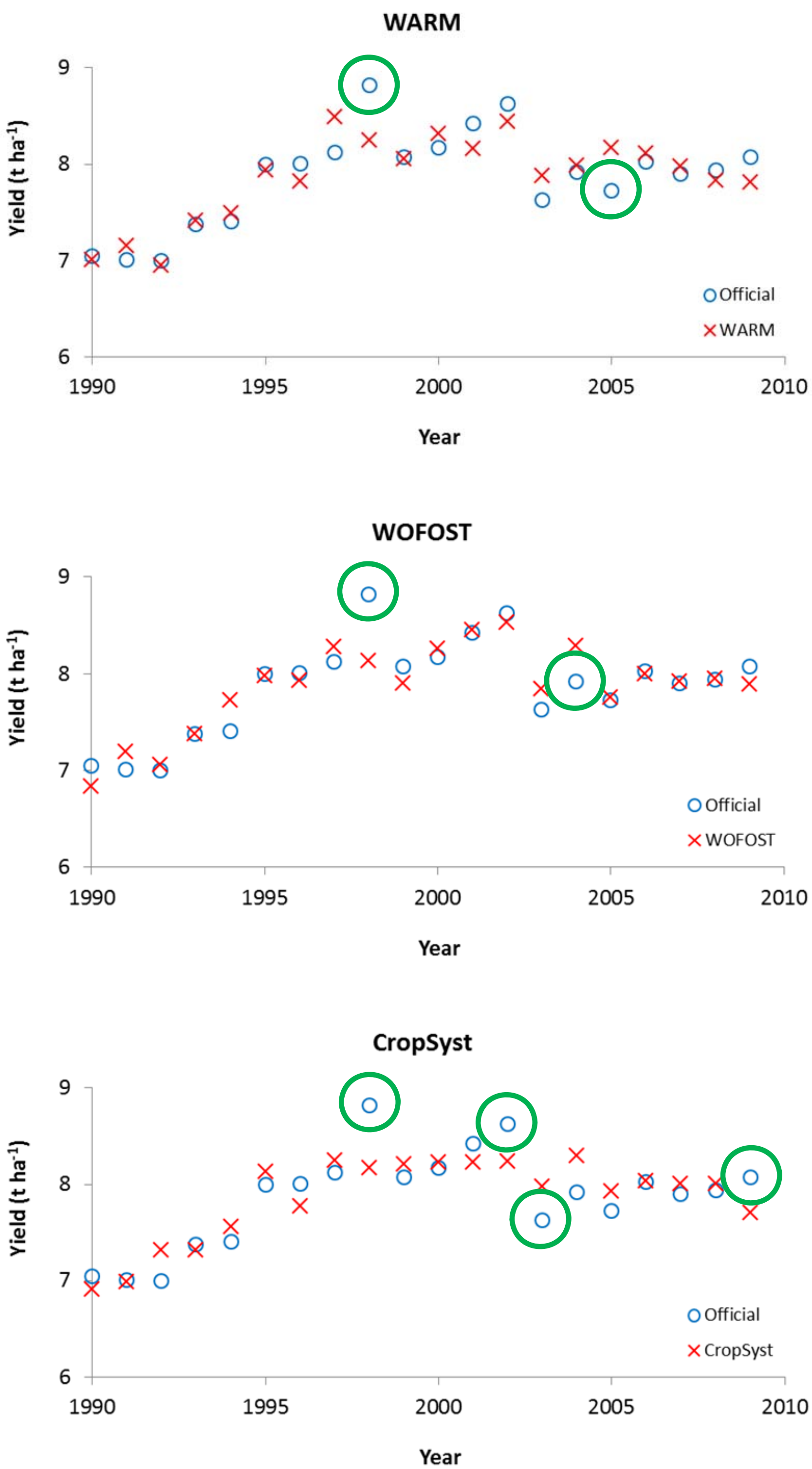

Figure 4 Multi-model monitoring; 1990-2009; decade: maturity -4.

Table 3 presents – for each of the evaluated forecasting time and for each model – the indicators selected by the stepwise regression procedure performed by the CGMS Statistical Toolbox. Indicators involved with the simulation of plant-pathogen interactions resulted crucial to explain inter-annual variability in official yields: at least two of them were always selected by the stepwise procedure.

It is interesting to notice that the number of infection events (indicator #7, "n. infections") – that was the only one not representing a state variable of the model – was selected in eight out of nine cases.

Table 3 Indicators selected by the stepwise regression performed between official yields and simulation outputs aggregated at province level; series 1990-2009.

WARM	WOFOST	CropSyst
Maturity is reached in all the simulation units		
1 (PAGB)[a]	1 (PAGB)	1 (PAGB)
3 (LAGB)[b]	7 (n. infections)[c]	7 (n. infections)
7 (n. infections)	8 (PLAI)[d]	8 (PLAI)
8 (PLAI)	9 (LLAI)[e]	9 (LLAI)
2 decades before maturity is reached in all the simulation units		
1 (PAGB)	1 (PAGB)	1 (PAGB)
3 (LAGB)	3 (LAGB)	3 (LAGB)
7 (n. infections)	7 (n. infections)	7 (n. infections)
9 (LLAI)	9 (LLAI)	9 (LLAI)
4 decades before maturity is reached in all the simulation units		
1 (PAGB)	1 (PAGB)	1 (PAGB)
7 (n. infections)	7 (n. infections)	3 (LAGB)
8 (PLAI)	8 (PLAI)	8 (PLAI)
9 (LLAI)	9 (LLAI)	9 (LLAI)

[a]: potential aboveground biomass
[b]: disease limited aboveground biomass
[c]: number of infection events
[d]: potential leaf area index
[e]: disease limited leaf area index

3.2. Time series 1990-2001

Results of multi-model approach for rice monitoring in Jiangsu for the climate conditions explored from 1990 to 2001 are shown in Table 4 and in Figures 5, 6 and 7.

In this case, WARM resulted always the model with the highest capability to reproduce official yield statistics, regardless of the moment during the crop cycle when the forecasting event was triggered (Table 4).

The expected increase in forecast reliability while approaching physiological maturity was not observed for WARM, that presented the highest accuracy for the forecast event performed two decades before maturity, whereas higher uncertainty was achieved for this model at the earliest and latest events.

Although WOFOST and CropSyst presented always lower values of the agreement metrics between official and forecasted yields compared to the other model, they always increased their accuracy while moving towards the end of the season.

WOFOST was always ranked third, despite its higher complexity (Confalonieri et al., 2009) and despite the good performances shown – especially for the latest event – when the forecasting event was performed using simulation outputs and official yields for the whole time series (see section "3.1. Time series 1990-2009" of this document).

A possible reason for this phenomenon is related to the robustness of the model with respect to the climate conditions explored. Confalonieri et al. (2010) already observed, for rice simulation in northern Italy, that the large number of freedom degrees during the calibration – due to the large number of model parameters – could lead to include in WOFOST parameters factors related to specific locations and seasons. This could lead to bad functioning when conditions changes, since model parameter should only include information on the morphological and physiological features of the plant, in turns lowering the robustness of the model/parameterization. This problem could likely explain the poor performances achieved by WOFOST for the time series 1990-2001, since climate conditions (Jiangsu, seasons 2011 and 2012) explored during calibration and validation activities at field level (see E-AGRI report D32.3) are more different to those explored during 1990-2001 compared to what they are with respect to the second part of the available time series.

Table 4 Multi-model rice monitoring in Jiangsu; results of the cross validation using the time series 1990-2001.

Decades before maturity is reached in all the simulation units	WARM	WOFOST	CropSyst
	R^2		
0	**0.96**	0.88	0.93
2	**0.98**	0.88	0.91
4	**0.95**	0.86	0.89
	RRMSE (%)		
0	**1.49**	2.57	2.03
2	**0.96**	2.59	2.26
4	**1.59**	2.80	2.43

Figure 5 presents the results of the comparison of official and forecasted yields for the time series 1990-2001. For the latest forecasting event (decade when the crop has reached maturity in all the elementary simulation units), the figure confirm the good performances achieved by WARM in terms of agreement metrics (Table 4). In this case, no significant under- or overestimations can be observed, and even the exceptional yield recorded in the province in 1998 were correctly reproduce by the model.

WOFOST presented – in general – good performance too, although it was not able to forecast the yields achieved when official statistics depicted a situation that markedly deviated from the trend. In particular, it decidedly underestimated the 1998 yield, and overestimated the bad season occurred in 1994.

A similar behaviour was observed for CropSyst, that showed a good accuracy but presented a marked overestimation in 2000 and a large underestimation in 1998.

The situation when forecasting events were triggered in earlier stages is similar – for WOFOST – to what discussed for the late one (Figure 6), whereas for CropSyst a lower overestimation was observed for 2000, although in this case the model slightly overestimated also the yield recorded in 1999 (Figure 7).

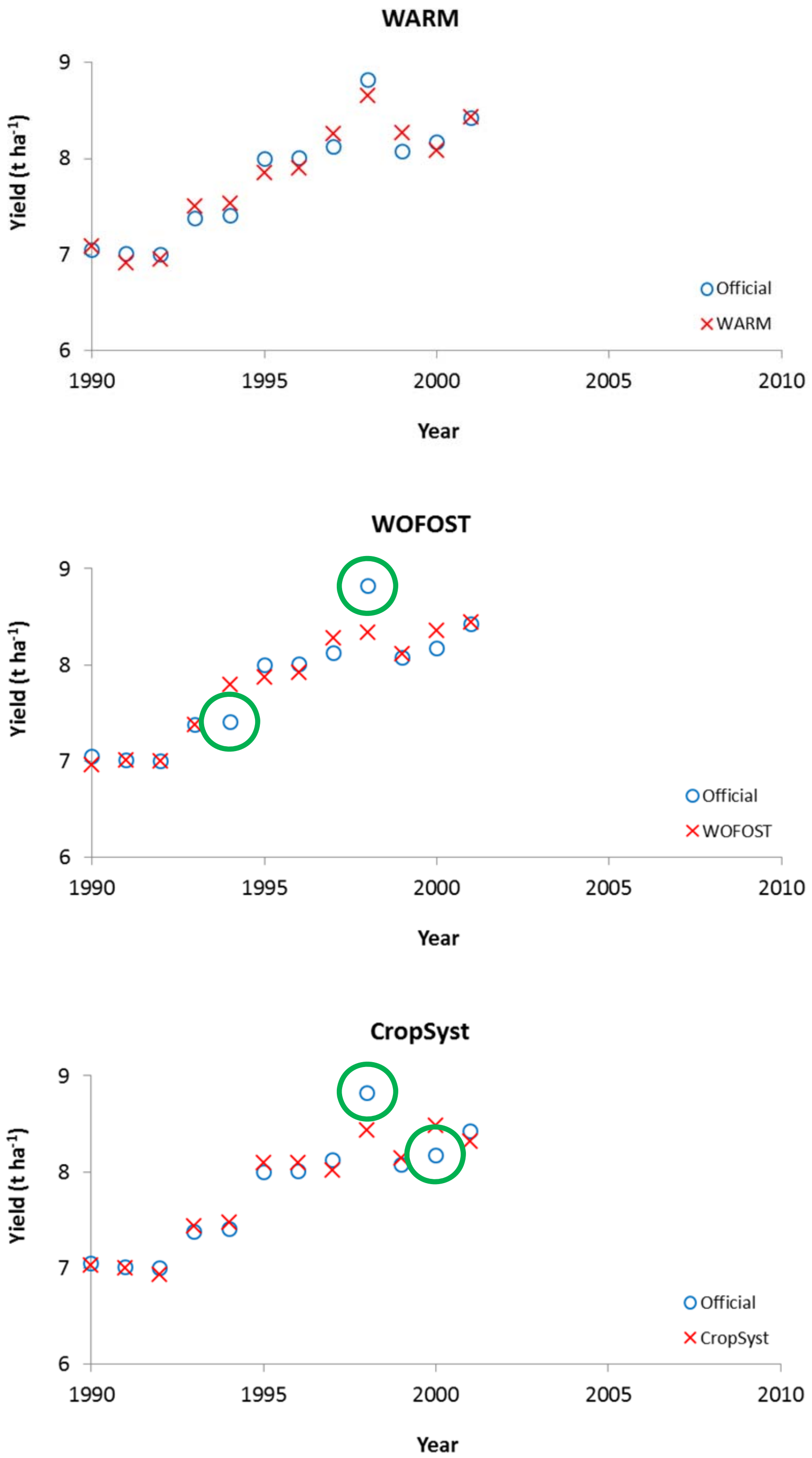

Figure 5 Multi-model monitoring; 1990-2001; maturity decade.

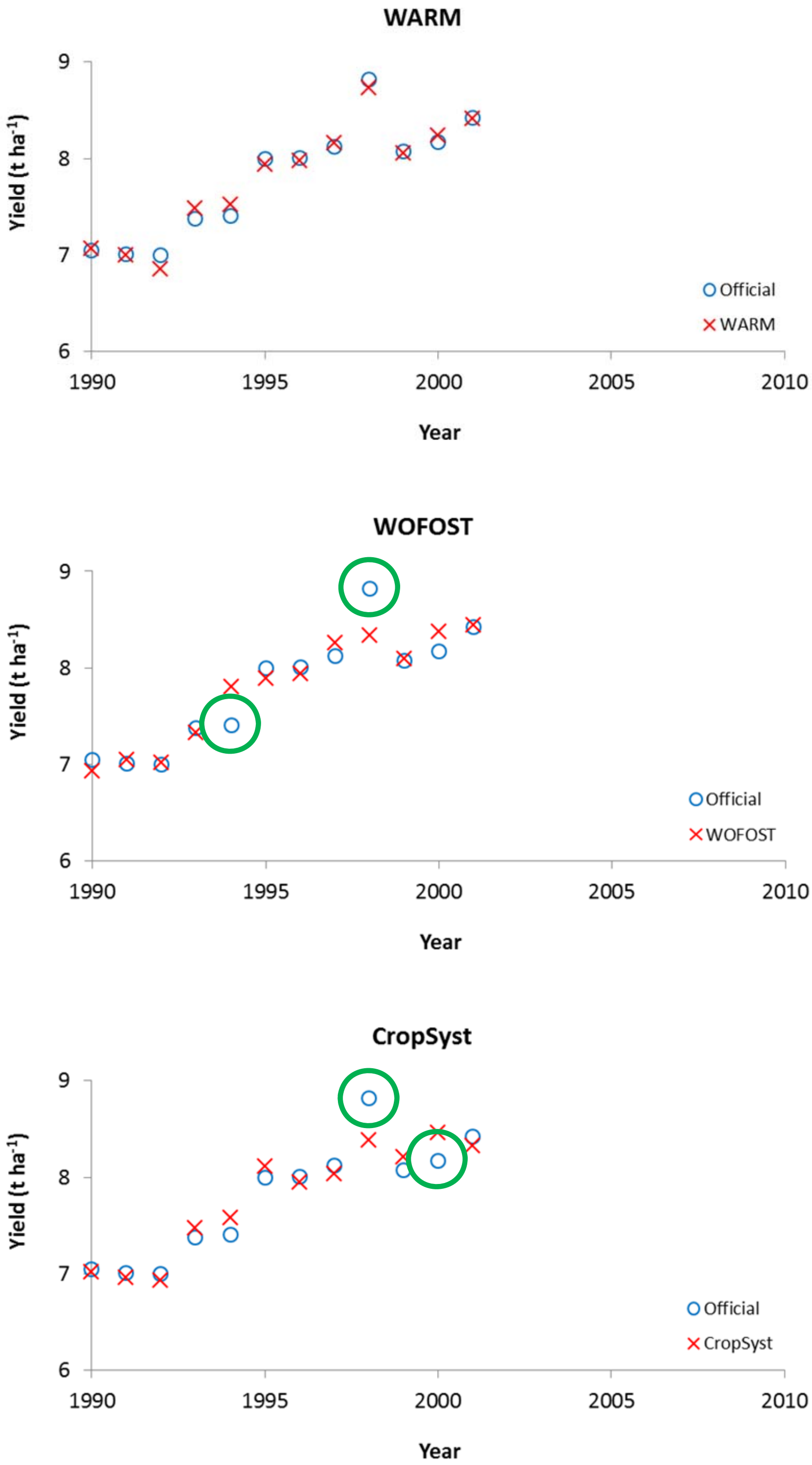

Figure 6 Multi-model monitoring; 1990-2001; decade: maturity -2.

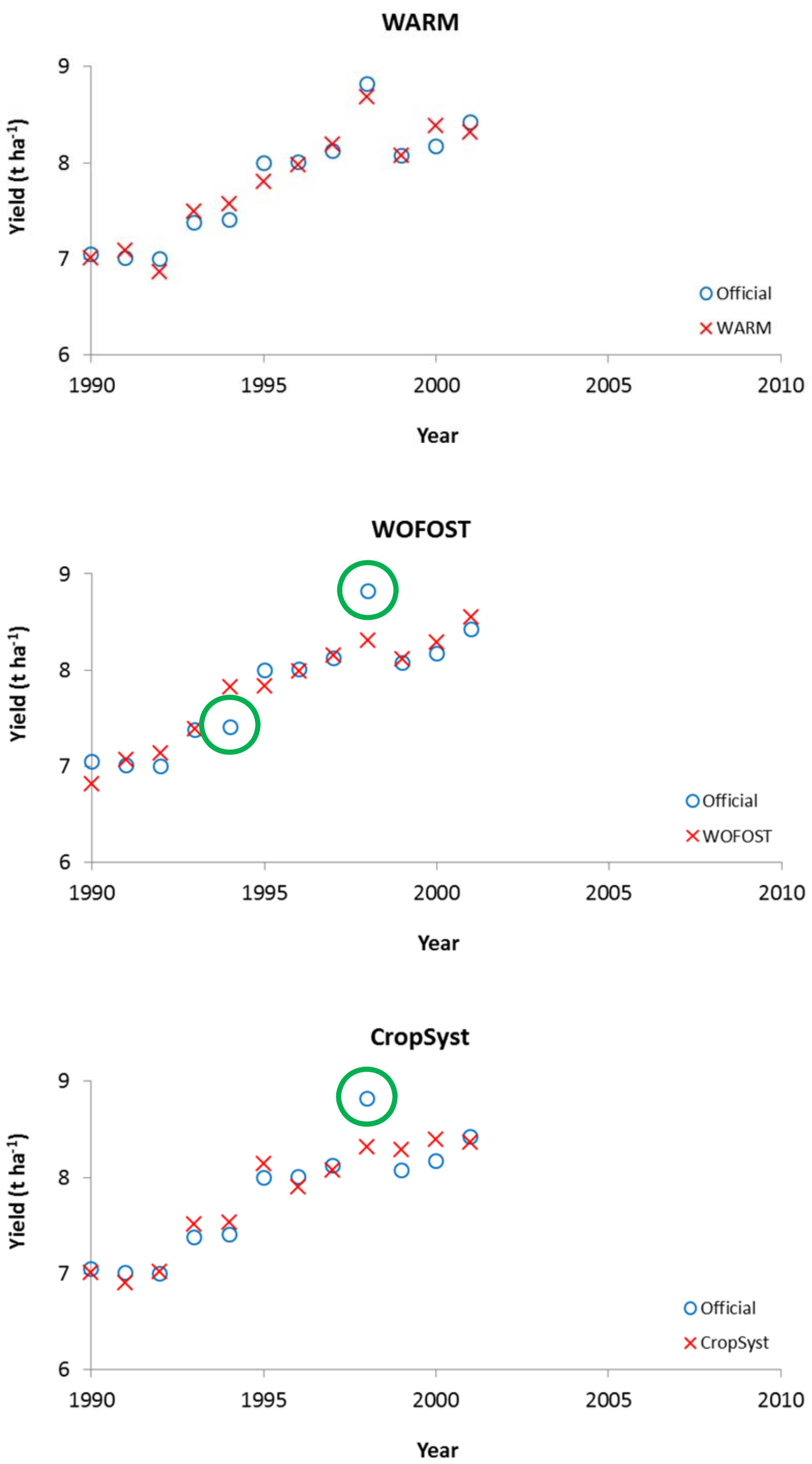

Figure 7 Multi-model monitoring; 1990-2001; decade: maturity -4.

Table 5 shows the indicators selected by the CGMS statistical post-processor for the historical series 1990-2001.

Compared to what observed for the whole time series (see Table 3), the relative importance of the selected indicators was more variable among the three crop models, with a higher importance of disease limited indicators. This could be due to the higher impact of diseases on official yields in the past (last decade of the XX century), likely because of a lower use of fungicides or – in general – because of a poorer technology adopted for disease control.

Table 5 Indicators selected by the stepwise regression performed between official yields and simulation outputs aggregated at province level; series 1990-2001.

WARM	WOFOST	CropSyst
Maturity is reached in all the simulation units		
1 (PAGB)[a]	3 (LAGB)[b]	3 (LAGB)
3 (LAGB)	7 (n. infections)[c]	7 (n. infections)
7 (n. infections)	8 (PLAI)[d]	8 (PLAI)
9 (LLAI)[e]	9 (LLAI)	9 (LLAI)
2 decades before maturity is reached in all the simulation units		
1 (PAGB)	1 (PAGB)	3 (LAGB)
3 (LAGB)	7 (n. infections)	7 (n. infections)
7 (n. infections)	8 (PLAI)	8 (PLAI)
8 (PLAI)	9 (LLAI)	9 (LLAI)
4 decades before maturity is reached in all the simulation units		
1 (PAGB)	1 (PAGB)	3 (LAGB)
3 (LAGB)	3 (LAGB)	7 (n. infections)
7 (n. infections)	8 (PLAI)	8 (PLAI)
9 (LLAI)	9 (LLAI)	9 (LLAI)

[a]: potential aboveground biomass
[b]: disease limited aboveground biomass
[c]: number of infection events
[d]: potential leaf area index
[e]: disease limited leaf area index

3.3. Time series 1998-2009

Results of the multi-model approach to rice monitoring in Jiangsu for the series 1998-2009 are shown in Table 6 and in Figures 8, 9 and 10.

This simulation/monitoring experiment was the one that produced the clearest evidences on the possible advantages deriving from multi-model runs. As shown in Table 6, the three moments when the forecasting events were triggered led to completely different rankings of the models according to the agreement between official and forecasted yields.

For the latest forecasting event, although the three models showed similar performances, CropSyst presented the highest reliability, with WARM and WOFOST ranked second and third, respectively, according to both the agreement metrics.

For the forecast event triggered two decades before maturity, WARM decidedly distanced the other two models, with values of relative root mean square error almost 0.5% better compared to those achieved by the other two crop simulators (CropSyst ranked second).

For the earliest forecasting event (four decades before maturity), WOFOST achieved the best values for both R^2 (0.94) and relative root mean square error (1.04%), confirming the higher reliability in case of monitoring activities far from the end of the season already shown when the entire historical series was analysed (see section 3.1. “Time series 1990-2009”). CropSyst – ranked first and second, respectively, for the events triggered at maturity and two decades before – presented, for the early forecast, the poorest reliability (R^2 = 0.80, relative root mean square error = 1.88%).

This experiment – based on analysis performed on the second part of the available historical series – can be considered as a perfect demonstration of the usefulness of the multi-model approach to crop monitoring and yield forecasting.

Table 6 Multi-model rice monitoring in Jiangsu; results of the cross validation using the time series 1998-2009.

Decades before maturity is reached in all the simulation units	WARM	WOFOST	CropSyst
	R^2		
0	0.90	0.89	**0.95**
2	**0.93**	0.84	0.87
4	0.82	**0.94**	0.80
	RRMSE (%)		
0	1.32	1.39	**0.94**
2	**1.07**	1.67	1.50
4	1.77	**1.04**	1.88

Figures 8, 9 and 10 show the agreement between official and forecasted yields for the three crop models and the three moments when the forecasting events were triggered.
Although CropSyst presented the highest accuracy, all the three models presented decidedly good performances for the late forecasting event (Figure 8), with just slight overestimations for WARM in 1999 and 2005 and for WOFOST in 2005. All the models were able to reproduce yields in the exceptional 1998 season, whereas problems for most of them were highlighted in this sense for the analysis performed using the whole historical series (1990-2009) and the first part of the available statistics (1990-2001).
For the forecasting event triggered two decades before maturity (Figure 9), WARM presented the highest capability of reproduce the inter-annual fluctuations in the official yield statistics, whereas both CropSyst and WOFOST revealed a relevant uncertainty, that was generalized for the former and concentrated in years markedly deviating from the trend for the latter (especially in 2002 and 2005).
The situation depicted in Figure 10 confirmed the good WOFOST forecasting capability in early crop stages already highlighted by the agreement metrics (Table 6). Both WARM and CropSyst, in this case, presented – in general – a lower reliability, with the former significantly overestimating the yields recorded in 2000 and 2005.

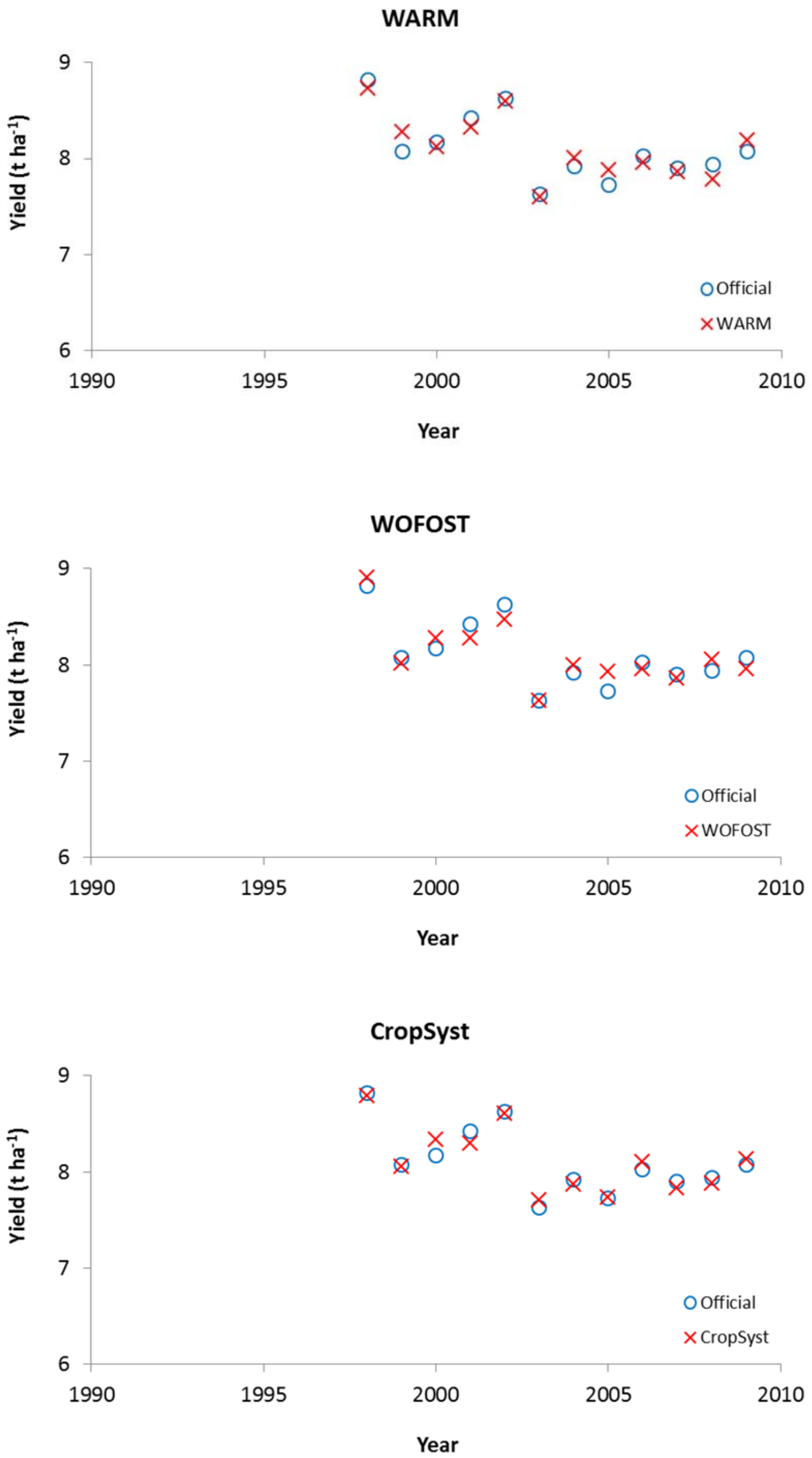

Figure 8 Multi-model monitoring; 1998-2009; maturity decade.

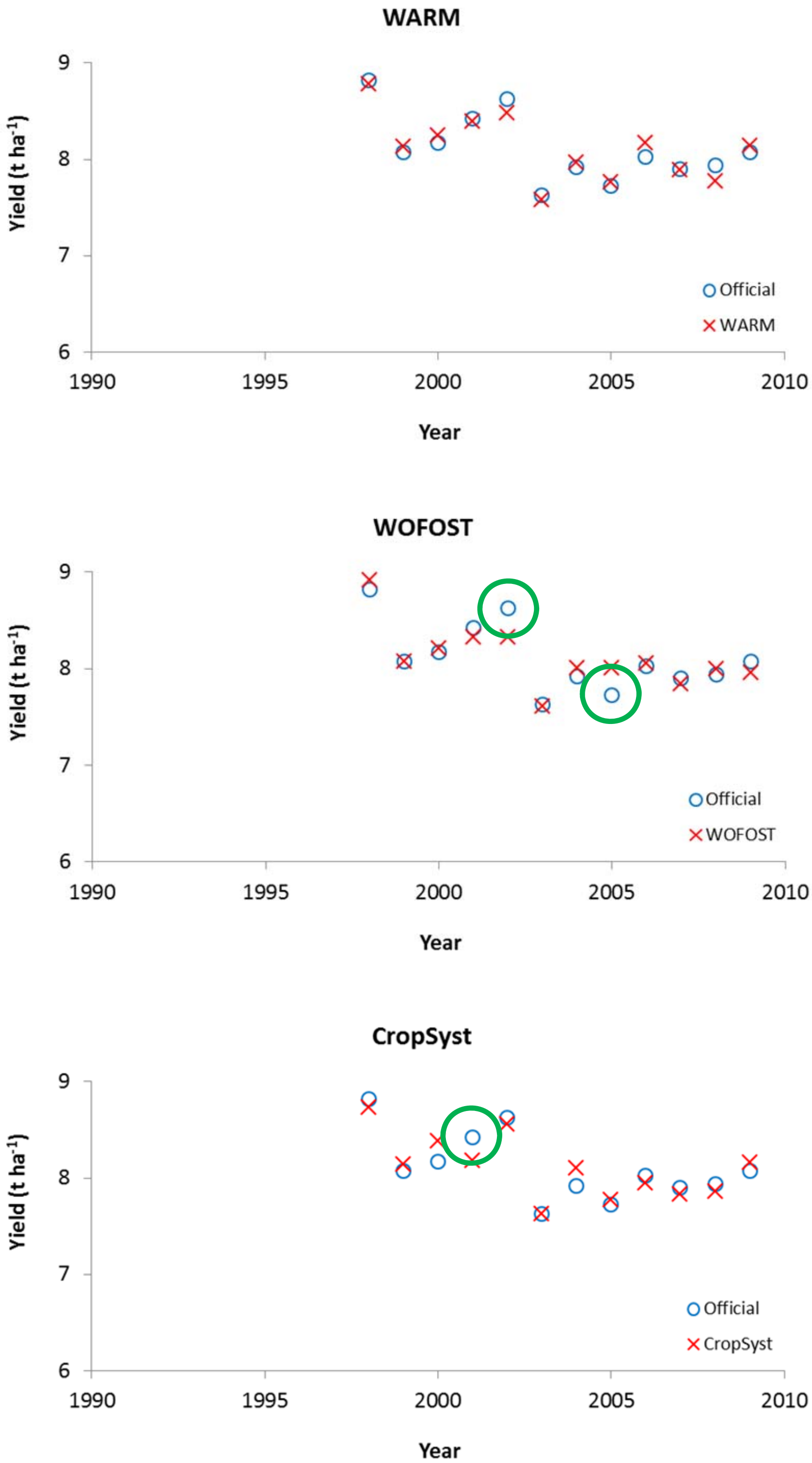

Figure 9 Multi-model monitoring; 1998-2009; decade: maturity -2.

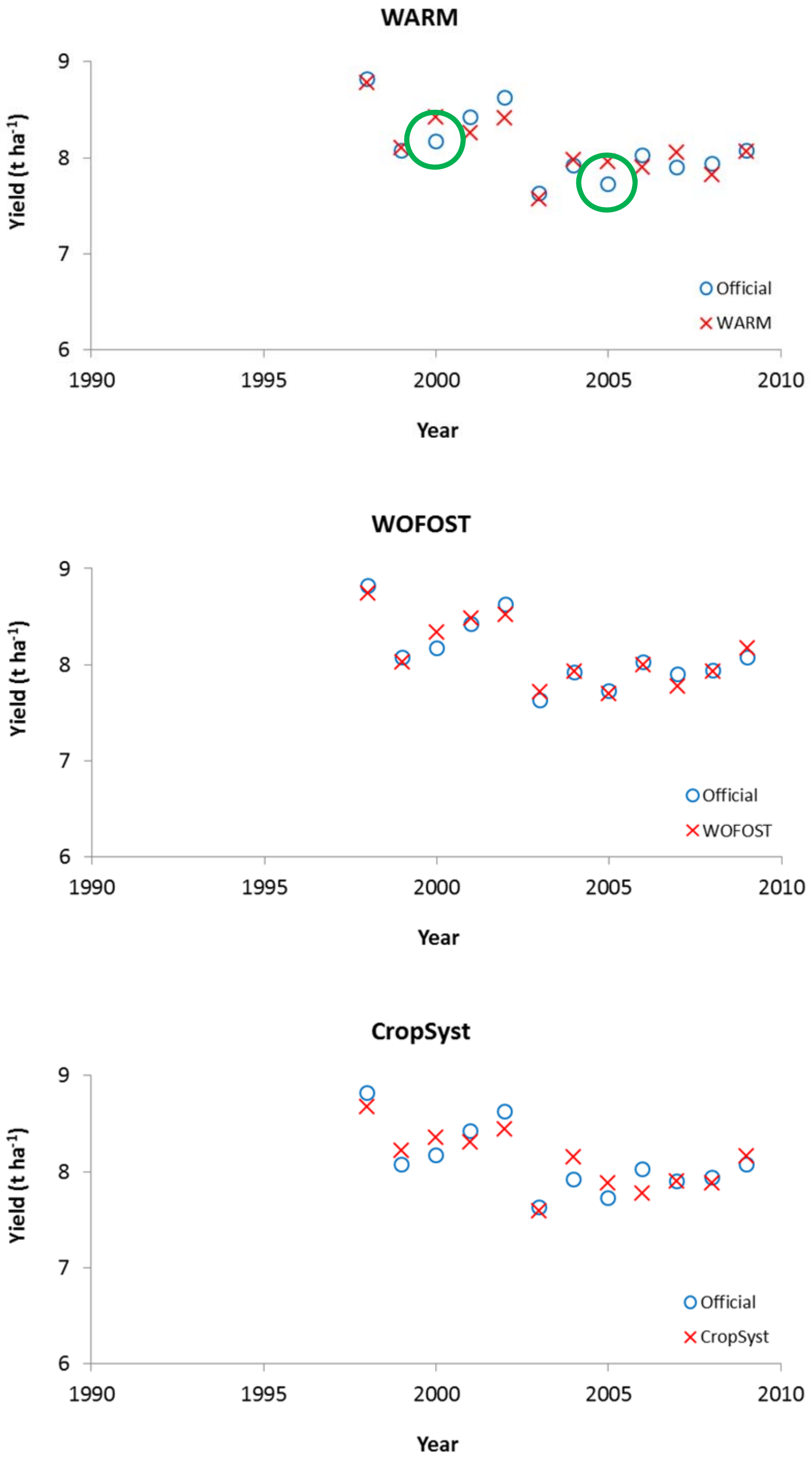

Figure 10 Multi-model monitoring; 1998-2009; decade: maturity -4.

Table 7 shows the indicators selected by the CGMS statistical post-processor. Compared to the analyses performed for the whole historical series and for the first part of the available official yield statistics, indicators involved with leaf area index presented a higher explanatory capability with respect with the variability in official yields. In one case – i.e., WOFOST × earliest forecasting event – this led to discard the indicator "number of infection events", always selected in all the other combinations crop model × monitoring time. As already observed for the analysis performed using the first part of the historical series, a great variability in the relative importance of the different indicators was highlighted while changing crop model and monitoring time.

Table 7 Indicators selected by the stepwise regression performed between official yields and simulation outputs aggregated at province level; series 1998-2009.

WARM	WOFOST	CropSyst
Maturity is reached in all the simulation units		
1 (PAGB)[a]	3 (LAGB)[b]	3 (LAGB)
3 (LAGB)	7 (n. infections)[c]	7 (n. infections)
7 (n. infections)	8 (PLAI)[d]	8 (PLAI)
9 (LLAI)[e]	9 (LLAI)	9 (LLAI)
2 decades before maturity is reached in all the simulation units		
3 (LAGB)	1 (PAGB)	1 (PAGB)
7 (n. infections)	3 (LAGB)	3 (LAGB)
8 (PLAI)	7 (n. infections)	8 (PLAI)
9 (LLAI)	8 (PLAI)	9 (LLAI)
4 decades before maturity is reached in all the simulation units		
1 (PAGB)	1 (PAGB)	1 (PAGB)
3 (LAGB)	3 (LAGB)	3 (LAGB)
7 (n. infections)	8 (PLAI)	7 (n. infections)
9 (LLAI)	9 (LLAI)	9 (LLAI)

[a]: potential aboveground biomass
[b]: disease limited aboveground biomass
[c]: number of infection events
[d]: potential leaf area index
[e]: disease limited leaf area index

4. Conclusions

According to the authors, this is the first time a multi-model approach was developed and evaluated for in-season monitoring and forecasting purposes.

Results demonstrated the usefulness of this approach, with different models achieving the best agreement metrics according to the climate conditions explored and to the time when the forecasting events were triggered.

All the crop models showed, however, satisfactory performances, thus demonstrating (i) the soundness of the approaches used to reproduce crop growth and development and (ii) the reliability of the parameterizations, in turns deriving from the high quality activities performed during the project for experimental data collection and calibration (E-AGRI reports D31.1 and D32.3).

This work also demonstrated the usefulness of simulating disease impact on crop yields, since disease-limited indicators were always selected by the CGMS statistical post processor, regardless from the crop model used and the time series considered.

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