

ACCEPTED MANUSCRIPT • OPEN ACCESS

An AgMIP framework for improved agricultural representation in IAMs

To cite this article before publication: Alex C Ruane *et al* 2017 *Environ. Res. Lett.* in press <https://doi.org/10.1088/1748-9326/aa8da6>

Manuscript version: Accepted Manuscript

Accepted Manuscript is “the version of the article accepted for publication including all changes made as a result of the peer review process, and which may also include the addition to the article by IOP Publishing of a header, an article ID, a cover sheet and/or an ‘Accepted Manuscript’ watermark, but excluding any other editing, typesetting or other changes made by IOP Publishing and/or its licensors”

This Accepted Manuscript is © 2017 The Author(s). Published by IOP Publishing Ltd.

As the Version of Record of this article is going to be / has been published on a gold open access basis under a CC BY 3.0 licence, this Accepted Manuscript is available for reuse under a CC BY 3.0 licence immediately.

Everyone is permitted to use all or part of the original content in this article, provided that they adhere to all the terms of the licence <https://creativecommons.org/licenses/by/3.0>

Although reasonable endeavours have been taken to obtain all necessary permissions from third parties to include their copyrighted content within this article, their full citation and copyright line may not be present in this Accepted Manuscript version. Before using any content from this article, please refer to the Version of Record on IOPscience once published for full citation and copyright details, as permissions may be required. All third party content is fully copyright protected and is not published on a gold open access basis under a CC BY licence, unless that is specifically stated in the figure caption in the Version of Record.

View the [article online](#) for updates and enhancements.

An AgMIP framework for improved agricultural representation in IAMs

Alex C. Ruane¹

Cynthia Rosenzweig¹

Senthold Asseng²

Kenneth J. Boote²

Joshua Elliott³

Frank Ewert^{4,5}

James W. Jones^{2,6}

Pierre Martre⁷

Sonali P. McDermid⁸

Christoph Müller⁹

Abigail Snyder¹⁰

Peter J. Thorburn¹¹

¹NASA Goddard Institute for Space Studies, New York, NY, USA

²University of Florida, Agricultural and Biological Engineering, Gainesville, FL, USA

³University of Chicago, Computation Institute, Chicago, IL, USA

⁴University of Bonn, Bonn, Germany

⁵Leibniz Center of Agricultural landscape Research (ZALF), Muencheberg, Germany

⁶National Science Foundation, Arlington, VA, USA

⁷UMR LEPSE, INRA, Montpellier SupAgro, Montpellier, France

⁸New York University, New York, USA

⁹Potsdam Institute for Climate Impact Research, Potsdam, Germany

¹⁰Pacific Northwest National Laboratory, College Park, MD, USA

¹¹Commonwealth Scientific and Industrial Research Organization, Brisbane, Australia

Submitted to *Environmental Research Letters* Special Issue:

Focus on an Inter-method Comparison of Climate Change Impacts on Agriculture

September 6th, 2017

Tweetable Abstract: Improved agricultural sector representation within IAMs requires collaborative development and application of crop models across scales.

Corresponding Author:

Alex Ruane

NASA Goddard Institute for Space Studies

2880 Broadway

New York, NY 10025

alexander.c.ruane@nasa.gov

Comment citer ce document : 1

Ruane, A. C., Rosenzweig, Asseng, S., Boote, Elliott, J., Ewert, F., Jones, Martre, P., McDermid, S. P., Müller, C., Snyder, A., Thorburn, P. J. (2017). An AgMIP framework for improved agricultural representation in integrated assessment models. *Environmental Research Letters*, 12.

DOI : 10.1088/1748-9326/aa8da6

Abstract

Integrated assessment models (IAMs) hold great potential to assess how future agricultural systems will be shaped by socioeconomic development, technological innovation, and changing climate conditions. By coupling with climate and crop model emulators, IAMs have the potential to resolve important agricultural feedback loops and identify unintended consequences of socioeconomic development for agricultural systems. Here we propose a framework to develop robust representation of agricultural system responses within IAMs, linking downstream applications with model development and the coordinated evaluation of key climate responses from local to global scales. We survey the strengths and weaknesses of protocol-based assessments linked to the Agricultural Model Intercomparison and Improvement Project (AgMIP), each utilizing multiple sites and models to evaluate crop response to core climate changes including shifts in carbon dioxide concentration, temperature, and water availability, with some studies further exploring how climate responses are affected by nitrogen levels and adaptation in farm systems. Site-based studies with carefully calibrated models encompass the largest number of activities; however they are limited in their ability to capture the full range of global agricultural system diversity. Representative site networks provide more targeted response information than broadly-sampled networks, with limitations stemming from difficulties in covering the diversity of farming systems. Global gridded crop models provide comprehensive coverage, although with large challenges for calibration and quality control of inputs. Diversity in climate responses underscores that crop model emulators must distinguish between regions and farming system while recognizing model uncertainty. Finally, to bridge the gap between bottom-up and top-down approaches we recommend the

Comment citer ce document : 2

1
2
3 deployment of a hybrid climate response system employing a representative network of
4 sites to bias-correct comprehensive gridded simulations, opening the door to accelerated
5
6 development and a broad range of applications.
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Comment citer ce document : 3

Ruane, A. C., Rosenzweig, Asseng, S., Boote, Elliott, J., Ewert, F., Jones, Martre, P.,
McDermid, S. P., Müller, C., Snyder, A., Thorburn, P. J. (2017). An AgMIP framework for improved
agricultural representation in integrated assessment models. *Environmental Research Letters*, 12.

DOI : 10.1088/1748-9326/aa8da6

1. Introduction

Integrated assessment models (IAMs) examine the interactions between human systems and the natural environment. IAMs thus explore how societal changes, such as global policies, population growth, socioeconomic development, greenhouse gas emissions, and technological advances affect land, air, and water resources, as well as repercussions when these natural resources are strained (Füssel et al., 2010; Clarke et al., 2014). Agriculture has long been central to the relationship between society and natural systems, providing vital foods, fiber, and energy while drawing heavily on land and water resources.

IAMs have traditionally represented agricultural sector changes as exogenous yield changes provided via scenarios aggregated to national or regional level production using current harvested area weights (Müller and Robertson, 2014; Nelson et al., 2013; Wiebe et al., 2015); however these only draw from a small subset of cutting-edge crop model assessments. A more direct coupling of agricultural responses within IAMs is facilitated by the application of crop model emulators, defined here as computationally-efficient representations of crop model results that capture fundamental responses to climate conditions. Crop model emulators may take the form of lookup tables (e.g., based upon response surfaces in Pirttioja et al., 2015), simplified response functions (Howden and Crimp, 2005; Crimp et al., 2008; Ruane et al., 2014; Makowski et al., 2015), or complex statistical models (Blanc, 2017; Mistry et al., 2017; Moore et al., 2017), each estimating yield as a function of climate variables with varying degrees of non-linearity and detail about the specific crop variety, farm environment, weather extremes, and crop model emulated. As these emulators get more complex the gain in computational efficiency

1
2
3 (compared to just using the crop model itself) is reduced, and in the end a crop model
4 emulator is limited by the performance of the crop model or crop model ensemble that it is
5 emulating. Emulators are distinct from statistical crop models, which are trained upon
6 observational data, with one advantage being that they may use principles of biophysical
7 process response to explore environments that have not been observed (such as future
8 climate and land use change). The exact specifications and desired detail of a crop model
9 emulator depends on the IAM to which it is coupled, the intended applications, and the
10 capabilities and coverage of the underlying crop model assessments.
11
12
13
14
15
16
17
18
19
20
21
22
23

24 IAMs have a lot to gain by better incorporating crop responses to changes in carbon dioxide
25 concentration ($[CO_2]$), temperature, water, nitrogen, and adaptation (CTWNA). CTWNA
26 sensitivity simulations can be more useful than projections driven by global climate models
27 (GCMs) as they provide the information basis to construct crop model emulators for use in
28 IAMs in conjunction with climate emulators (e.g., Meinshausen et al., 2011; Castruccio et
29 al 2014; Hartin et al., 2015). **Figure 1** illustrates how this powerful combination improves
30 agricultural sector representation by allowing IAM land use changes and emissions of
31 greenhouse gases and aerosols to influence regional temperature and precipitation changes
32 (using the climate emulator), affecting crop production and requirements (using the crop
33 model emulator) that feed back into the IAM. This also captures agricultural feedback
34 loops, where societal or environmental changes alter the climate and shift agricultural
35 production in a manner that reinforces or diminishes those changes, and unintended
36 consequences when policies in another sector or region impact distant farming systems
37 (potentially through climate responses or through independent mechanisms such as trade).
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1
2
3
4
5
6 The Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig
7 et al., 2013, 2015) was launched in 2010 to provide a common framework and systematic
8 approach for analysis of agricultural challenges. AgMIP connects climate, crop, livestock,
9 and economic models at local, regional, and global scales, allowing multi-model, multi-
10 discipline, multi-scale assessments of agricultural development and food security
11 (Rosenzweig et al., 2016; Antle et al., 2015). AgMIP mainly utilizes process-based crop
12 models that represent biophysical processes and their responses to genetics, environment,
13 and management over the course of a growing season, with statistical models also included
14 in some efforts. Integrated assessment modelers examining previous crop modeling studies
15 have been challenged to make sense of differing assumptions, methods, and models in
16 addition to the under-representation of agricultural systems beyond the mid-latitude, high-
17 input breadbaskets (White et al., 2011; Challinor et al., 2014a). AgMIP facilitates more
18 robust and transferable findings based on common simulation protocols, multi-model
19 ensembles, the tracking of uncertainty, and an emphasis on under-simulated farm systems.
20 Great strides in computational power are opening new doors for agricultural model
21 development and application, raising the ceiling for multi-model analyses, new scales of
22 decision support, and more accurate crop model emulators for IAM applications.
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47

48 This article takes stock of the methods used by AgMIP to capture the response of
49 agricultural productivity to changing climate conditions, examining the relative strengths
50 and weaknesses of site, network, and gridded modeling approaches to inform IAMs and
51 related crop model emulators. We then provide a framework for coordinated development
52
53
54
55
56
57
58
59
60

1
2
3 and application of agricultural responses drawing value from local to global approaches
4 and linking biophysical and integrated assessments. We conclude with recommendations
5
6 for priority future work and applications.
7
8
9

10 11 12 **2. Survey of Crop Model Outputs Germane to IAM Emulators** 13

14
15 Although AgMIP conducts more than 30 activities (Rosenzweig et al., 2015), here we
16 survey activities that (a) test for sensitivity to some or all of CTWNA factors and utilize
17 (b) multiple agricultural models, (c) multiple sites, and (d) common protocols. These are
18 described in **Table 1** along with related activities by the MACSUR project (Modelling
19 European Agriculture with Climate Change for Food Security; Ewert et al., 2015). **Figure**
20 **2** presents the geographic coverage of these site, network, and gridded activities.
21
22
23
24
25
26
27
28
29
30
31

32 **2.1 Site-Based Approaches** 33

34 The overwhelming majority of studies in the large literature on crop impacts are site-based
35 studies (White et al., 2011; Challinor et al., 2014a), but inconsistent protocols, assumptions,
36 geographic sampling, and methods make generalized interpretation of the results difficult.
37 AgMIP's emphasis on model intercomparison and exploration of climate responses drove
38 initial research activities toward species-based assessment at a small number of carefully
39 selected sites. These 'pilot' projects organized around the application of multiple models
40 on high-quality field datasets (Boote et al., 2015; Kersebaum et al., 2015) to expose
41 differences in model structure, process responses, data requirements, and input/output
42 formats.
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1
2
3 The first crop pilot was organized by the AgMIP Wheat Team, in which 27 modeling
4 groups ran historical simulations and 30-year sensitivity tests for [CO₂], temperature, and
5
6 nitrogen (CTN) response at sites in the Netherlands, India, Argentina, and Australia
7
8 (Asseng et al., 2013; Martre et al., 2015). The Wheat Pilot was open to all interested
9
10 modeling groups as long as their models were published in peer-reviewed articles.
11
12
13
14
15

16
17 Similar multi-model crop pilots were conducted across selected sites by AgMIP Maize (CT
18 responses; Bassu et al., 2014), AgMIP Rice (CT responses; Li et al., 2015), AgMIP Potato
19
20 (CTW responses; Fleisher et al., 2016), AgMIP Sugarcane (CTW responses; Marin et al.,
21
22 2015), and AgMIP Canola (CTWN responses; Wang et al., personal communication).
23
24 MACSUR also analyzed TW responses at a transect of four European wheat sites,
25
26 providing continuous impacts response surfaces that characterize fundamental crop model
27
28 properties (Pirttioja et al., 2015; Fronzek et al., 2017), and examined the CN response of
29
30 crop rotations (Kollas et al., 2017; Yin et al., 2017). AgMIP's Livestock and Grasslands
31
32 Team used individual models at a number of sites to create CTW responses surfaces for
33
34 yield and greenhouse gas balances (Fiona Erhardt, personal communication). Phase 2
35
36 studies by AgMIP Wheat, Maize, and Rice teams have challenged models with field
37
38 experiments that gauge climate sensitivity at test sites, utilizing "Hot Serial Cereal" heat
39
40 stress experiments for wheat (Asseng et al., 2015a; Webber et al., 2017) and Free-Air
41
42 Carbon Enrichment (FACE) data to explore [CO₂] response in maize (Durand et al., 2017)
43
44 and rice (Hasegawa et al., personal communication) (**Table 2**). CTWN sensitivity
45
46 experiments also form a key component of AgMIP's regional integrated assessments at
47
48 sites across South Asia and Sub-Saharan Africa (Rosenzweig et al., 2017).
49
50
51
52
53
54
55
56
57
58
59
60

2.1.1 Strengths and weaknesses of site-based approaches

Intensive, multi-model intercomparisons at high-quality pilot field sites are a critical first component of model evaluation, yielding valuable insight into process responses, structural biases, data requirements, and performance across contrasting systems. These analyses are anchored in field data that enable validation of state variables (e.g., leaf-area index; above-ground biomass and N contents; plant-available soil moisture) across a number of phenological stages as well as end-of-season characteristics (e.g., grain yield and protein content, harvest index). This allows evaluation of the mechanisms by which plants respond to environmental changes, highlighting sensitive biophysical processes and growth stages that in turn help focus climate projections on fundamental stresses (e.g., drought in reproductive stages; heat stress at anthesis). Results demonstrate that multi-model ensembles consistently outperform individual models when evaluated across variables and sites (Martre et al., 2015; Asseng et al., 2013; Bassu et al., 2014; Li et al., 2015; Fleisher et al., 2016), although at any given site a subset of models may be preferred (Castañeda-Vera et al., 2015).

Site-based assessments from the initial AgMIP Pilots are limited in their application to IAMs as they cover only a small number of sites and farming systems. As expected, crops responded differently at the selected sites owing to unique soils, weather, cultivars, and farm management. Additional careful sampling of interactions across the broader CTWNA space is needed, as shown by the benefits of elevated [CO₂] for water use efficiency in

1
2
3 recent AgMIP crop team activities (Cammarano et al., 2016; Deryng et al., 2016; Durand
4 et al., 2017).
5
6
7
8
9

10 **2.2 Network-based Approaches**

11
12 As AgMIP protocols were developed and tested on individual sites, the next step scaled up
13 these approaches through larger networks of sites coordinated to ensure adherence to a
14 common protocol that enables direct comparison.
15
16
17
18
19

20 **2.2.1 Wide *ad hoc* network approach**

21
22 AgMIP launched the Coordinated Climate-Crop Modeling Project (C3MP; Ruane et al.,
23 2013; McDermid et al., 2015a), to create CTW impact response surfaces at a range of sites
24 around the world. C3MP samples the CTW space projected by GCMs in the 21st century,
25 enabling the fitting of emulators and response surfaces that can be rapidly applied to
26 estimate the agricultural impacts of new climate projections. C3MP created information
27 technology tools and templates to facilitate the process and invited the agricultural
28 modeling community to participate with their own calibrated sites. The resulting archive
29 reflects submissions from 100 crop modelers, with 1137 simulation sets from 55 countries,
30 including results from 19 crop model families and 18 crop species (McDermid et al.,
31 2015a).
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50

51 **2.2.1.1. Strengths and weaknesses of wide *ad hoc* networks**

52
53 C3MP's open call for crop model participation led to an unprecedented number and
54 diversity of contributed simulation sets but also challenges in analyses. The result is a
55
56
57
58
59
60

1
2
3 network of voluntary ‘crowd-sourced’ responses rather than a designed plan of geographic
4 coverage, representative sites, or multi-model analyses. Nevertheless, C3MP’s wide *ad*
5 *hoc* network covers most major agricultural lands and features models calibrated with site-
6 specific information (Fig. 2). Sampling across all submitted results for a given category of
7 system (e.g., rainfed maize) provides CTW response surfaces isolating the common yield
8 response across a broad sampling of sites and systems as well as uncertainty stemming
9 from model, soil, baseline climate, cultivar, and farming system differences (McDermid et
10 al., 2015a). Recognizing that IAMs typically track major crops (wheat and rice) and
11 commodity groups (e.g., oil seeds, coarse grains, sugar crops, fruits & vegetables), C3MP’s
12 relatively large number of crop species also reduces the amount of crop response mapping
13 that is required to represent climate responses across the diversity of agricultural
14 commodities. C3MP is particularly useful in distinguishing responses within a commodity
15 group (for example, differentiating between millet, sorghum, and maize responses for
16 coarse grains).

17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39 Aggregation of the C3MP archive to global production responses is challenging given
40 geographic gaps and under-represented systems, and vetting is difficult given its reliance
41 on prior model calibration and a skew toward common crop models (as were also
42 challenges in the Challinor et al., 2014a, meta-analysis). We recommend that C3MP
43 analyses do not include simulation sets that use antiquated model versions and a small
44 percentage of flagged sites where low historical yields indicate farming systems that are
45 not presently viable. In some cases, these were conducted as tests of land uses that may
46 become viable in wetter and high-[CO₂] futures, but must be considered distinct from
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1
2
3 broader CTW analyses. C3MP remains an open process, and each new submission
4 increases the robustness of ensemble statistics and analyses.
5
6
7
8
9

10 **2.2.2 Representative network approach**

11 AgMIP Wheat Phase 2b created a global network of 30 well-watered sites selected to
12 represent major wheat systems and regional production areas (irrigated and high-rainfall
13 wheat crops contribute ~70% of global production; see Fig. 2) (Asseng et al., 2015a). 30
14 wheat models are configured for simulation of CT responses at each site, allowing robust
15 ensemble projections and uncertainty analyses (Wallach et al., 2015; 2016).
16
17
18
19
20
21
22
23
24
25
26

27 **2.2.2.1 Strengths and weaknesses of representative networks**

28 The AgMIP Wheat Team network is distinct from C3MP's *ad hoc* network in that its design
29 allows multi-model assessment on major regional production systems that together
30 generate the large majority of global wheat production (Table 2). Simulated relative
31 impacts are applied to recent FAO country production statistics associated with each
32 simulated location to up-scale to global production impacts (Asseng et al., 2015a; Liu et
33 al., 2016).
34
35
36
37
38
39
40
41
42
43
44
45

46 Even with 30 sites, the network is limited in its spatial coverage and individual sites may
47 not reflect conditions in the broader production regions they represent. The network is
48 concentrated in high-production zones and is likely to miss important responses in areas
49 that were not simulated (AgMIP-Wheat Phase 3 will fill some of these gaps for water-
50 stressed systems). As a simple metric of comprehensiveness of coverage, **Figure 3** shows
51
52
53
54
55
56
57
58
59
60

1
2
3 how the rainfed and irrigated wheat networks from C3MP and AgMIP-Wheat Phase 2
4 cover wheat-growing climate conditions as compared with the global Monthly Irrigated
5 and Rainfed Crop Area (MIRCA) year 2000 dataset (Portmann et al., 2010), using
6 AgMERRA climate data (Ruane et al., 2015a) and growing seasons from the Global
7 Gridded Crop Model Intercomparison (GGCMI; Elliott et al., 2015). Both networks are
8 most dense in climate zones that are prominent for wheat production; however the larger
9 C3MP network also includes less common climates for rainfed wheat and samples more
10 from the tails of the irrigated wheat distribution than does AgMIP-Wheat. By simulating
11 more of the cool and wet tails it is likely that C3MP captures more farms that potentially
12 benefit from increases in temperature or are less vulnerable to decreases in precipitation.
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28

29 Regions with high levels of diversity are difficult to capture given limitations in
30 representative site networks. Sentinel crop modeling sites are often calibrated with data
31 from field experiment datasets designed to highlight potential genetic, fertilizer, water, or
32 pest control treatments, and therefore may not be representative of prevailing agricultural
33 systems within that production region. These site networks tend to be more useful when
34 examining the percentage yield response to a given climate change; this metric has proven
35 robust even in the face of persistent bias in mean regional yields (Challinor et al., 2014b;
36 Asseng et al., 2015a).
37
38
39
40
41
42
43
44
45
46
47
48
49
50

51 **2.3 Global approaches**

52 Advances in high-performance computing have allowed crop models to enter a new phase
53 of development that is nearly unconstrained by computational limitations. While IAMs are
54
55
56
57
58
59
60

1
2
3 typically run on desktop computers or simple clusters, the 18 modeling groups participating
4 in AgMIP's Global Gridded Crop Modeling Intercomparison (GGCMI; Table 3) use
5 parallel computing and advanced data processing pipelines to conduct protocol-based
6 simulations on a 0.5° x 0.5° global grid (Rosenzweig et al., 2014; Elliott et al., 2015), with
7 higher resolution gridded studies in the works. These outputs therefore form a desirable
8 basis for more computationally-efficient IAM application through emulators. GGCMI
9 Phase 2 performs a systematic analysis of CTWNA sensitivities for rainfed and irrigated
10 maize, rice, wheat, and soybean with consistent climate information and harmonized
11 planting dates. Adaptation is examined by shifting cultivars to maintain the growing period
12 even as warmer temperatures accelerate phenologic development, thus offsetting some
13 yield losses from climate change.
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31

32 **2.3.1 Strengths and Weaknesses of Global Approaches**

33
34 GGCMI's fast-track results (Table 3) provide biophysical impacts across emissions
35 scenarios and 5 GCMs (Rosenzweig et al., 2014), providing applications with ensemble
36 mean impacts and uncertainty information from 7 GGCMs for 4 crop species (maize,
37 wheat, rice, and soybean) across the global grid (Nelson et al. 2014; Wiebe et al. 2015;
38 Villoria et al. 2016). It is difficult for crop model emulators to disentangle fundamental
39 responses from these outputs, however, given the many types of changing and interacting
40 climate conditions (e.g., mean temperatures and rainfall; sub-seasonal variations; extreme
41 events). Emulation is also complicated by the inclusion of responsive adaptations allowing
42 management to evolve with climate change in some participating models (Rosenzweig et
43 al., 2014, supplementary).
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

GGCMI Phase 2 findings indicate considerable spatial variation in CTWNA response across different environments and farm systems, exemplified by the response of rainfed maize to higher [CO₂] and temperature in the parallel-DSSAT crop model (pDSSAT; Elliott et al., 2014) (**Figure 4**). These results provide a convenient basis for the construction of crop model emulators, and can also be connected to economic and/or resource availability drivers from IAMs to dynamically characterize the evolution of socioeconomic yield gap factors such as fertilizer use, irrigation, and adaptation potential.

In contrast to the site networks, GGCMs rely on gridded soil, genetic, management, and weather datasets designed to capture spatially-averaged conditions rather than conditions on a particular farm (Elliott et al., 2015). While the 0.5° x 0.5° spatial resolution used within GGCMI is finer than many GCMs, a grid cell on the equator represents >310,000 ha and thus poses a challenge for comprehensive farm system calibration.

GGCM results are often evaluated using regional yield and production reports, with trend adjustment recommended in recognition of technological development and processes that are not explicitly modeled such as pests, diseases, and widespread flooding (Müller et al., 2017). Analogously, statistical crop response models are occasionally fitted to similar aggregate yield data that may reflect embedded abiotic factors (e.g., Lobell et al., 2011). Bias-adjustment is a recommended for GGCM application in IAMs, similar to common practices for climate model output applications (e.g., Wilby et al., 2004; Ruane et al., 2015b). Overall, GGCMs reflect that there are larger uncertainties in developing country

1
2
3 and low-input farming systems, and stand to benefit from improved data collection and
4 sharing in application regions (Kihara et al., 2015; McDermid et al., 2015b).
5
6
7
8
9

10 **2.4. Emergent characteristics and opportunities from CTWNA simulations**

11 AgMIP site, network, and gridded results demonstrate that multi-model ensembles
12 outperform individual models when analyzed across multiple sites and evaluation variables
13 (e.g., Asseng et al., 2013; Rosenzweig et al., 2014; Martre et al., 2015; Li et al., 2014;
14 Bassu et al., 2014; Wallach et al., 2015; Ruane et al., 2016; Fleisher et al., 2016). Liu et
15 al. (2016) found relative agreement in wheat response to a 1 °C rise in global temperature,
16 with multi-model ensembles in the well-watered AgMIP Wheat network, GGCM1's
17 ISIMIP fast-track, and several statistical model approaches finding 4.1-6.4% declines in
18 global production.
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33

34 Uncertainties in input data indicate that there is still room for harmonization that will
35 improve consistency, as illustrated by a comparison of growing seasons at the well-watered
36 AgMIP-Wheat network sites and corresponding GGCM1 grid cells (**Figure 5**). Uncertainty
37 owing to model structure and parameters remains substantial, and differences in CTWNA
38 responses by two modelers using the same DSSAT model within the MACSUR IRS and
39 AgMIP-Wheat Phase 1 also highlights the potential role of modeler uncertainty stemming
40 from assumptions and subjective decisions made in the absence of supporting data
41 (Pirttioja et al., 2015; Confalonieri et al., 2015). We therefore advise applications to
42 recognize the uncertainty in model-based responses through the use of emulators derived
43 from multiple models or an imposed error term scaled to model-based uncertainty.
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Evidence across AgMIP activities also recommends avoidance of universal yield functions in favor of yield response functions fitted to broad agro-ecological zones and farming systems (e.g., defined by fertilizer and irrigation inputs).

3. AgMIP framework for improved agricultural representation in IAMs

A cascading pathway of development underlies agricultural representation in IAMs, forming a framework that may be used to drive coordinated development of “simulation levels”, here defined as common communities of development including site-based crop models, network and gridded models, crop model emulators, and eventual IAM applications (**Figure 6**). Close collaboration and regular updates between site, network, and gridded crop modelers, emulation experts, and IAM groups are needed to keep agricultural impact applications on the cutting edge, to facilitate the use of multiple models, to incorporate understanding from multiple modeling groups, and to avoid the propagation of known biases.

Each simulation level in the AgMIP Framework benefits from improved data access and innovations in core methodologies. Investment in research and development is well served by matching the design, capabilities, and development priorities of models and tools at each level in Figure 6. In particular, new biophysical process understanding is best developed within site-based models using field experiment data, particularly for under-sampled agro-ecological zones, crop species, and farming systems under various intensifications (Challinor et al., 2015; Maiorano et al., 2017). Networks and gridded models gain from new datasets that allow extensive configuration for many sites and

1
2
3 systems, and have tremendous potential to apply advanced bias-correction and aggregation
4 approaches (Challinor et al., 2014; van Bussel et al., 2016; Hoffmann et al., 2015, 2016;
5 Zhao et al., 2015, 2016). Crop model emulators are progressed with improved statistical
6 efficiencies and the availability of observed agricultural response data for evaluating
7 strengths and weaknesses. In addition to the potential benefit of adding improved crop
8 model emulators, IAM simulations of long-term shifts in agricultural production are
9 furthered by good data on current systems and advanced representation of the implications
10 of agricultural investment and technological development.
11
12
13
14
15
16
17
18
19
20
21
22
23

24 The AgMIP framework for improved agricultural representation in IAMs is non-linear as
25 lower simulation levels build upon advances higher up in the framework and high levels
26 also receive critical feedback from downstream simulation levels. Pathways of upstream
27 improvements include that assessments of improved models on established grids and
28 networks provide vital feedback for site-based model development on diverse sites.
29 Likewise, emulators often spotlight key sensitivities and uncertainties that may spur further
30 site-based model development and the creation of more representative networks. Network
31 and gridded studies examine the biophysical viability of various simulated farm systems to
32 determine land use pressures, but benefit tremendously by incorporating information on
33 economic viability and resource constraints that IAMs can provide. It is also important to
34 note that many of these simulation levels have extensive applications beyond agricultural
35 representation in IAMs, and that the key bottleneck for one applications may differ from
36 another's crucial development priority.
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

4. Priority Future Development and Applications

Analysis of the multi-model, multi-site climate sensitivity datasets reviewed in this study suggest that IAMs and other large-scale applications would be well served by the creation and systematic development of a hybrid CTWNA response system that blends the strengths of network and gridded approaches (as noted in Figure 6). This hybrid response system would be rooted in (1) detailed process understanding across a representative network of well-calibrated field sites (ideally using field data from prevailing management systems) combined with (2) comprehensive CTWNA coverage from gridded models. Baseline responses generated by these gridded models could initially be compared against the corresponding representative network simulations to assess methodological uncertainty and calculate bias-correction factors. Bias-corrected gridded results could then provide an information basis for crop model emulators and IAM applications, characterizing different farming systems using nitrogen and water components of the CTWNA analysis.

Table 1 highlights that progress toward the creation of this hybrid response system is most advanced for wheat, given the AgMIP-Wheat Phase 2b representative network and spring and winter wheat simulations within GGCM Phase 2. In contrast, soybean is simulated in GGCM but has not yet been the focus of site- or network-based CTWNA analysis, and a number of other important commodities merit inclusion. Coordinated and systematic development of the hybrid response system would foster rapid iterative improvements, as research groups improve the hybrid framework by contributing new process understanding, field sites, model runs, regional configuration information, or statistical approaches. An expanded representative network of models and a fully configured high-resolution gridded

1
2
3 (or geo-referenced polygon) model will eventually be interchangeable; however this hybrid
4
5 response system provides current state-of-the-art responses and a practical roadmap for
6
7 applications.
8
9

10
11
12 Coordination across AgMIP activities supports the development of linked global and
13
14 regional assessments to address agricultural sector challenges and food security
15
16 (Rosenzweig et al., 2016). Inclusion of IAMs would bring these to a new level, although
17
18 it is critical that these account for lingering model uncertainty and data gaps even as these
19
20 are addressed through the coordinated development of agricultural response in linked
21
22 models.
23
24
25
26
27
28

29 **Acknowledgements**

30
31 We are grateful for the tremendous effort and contributions provided by all modelers and
32
33 leaders of all projects listed in Table 1. This letter was motivated by discussions with
34
35 members of the Program on Integrated Assessment Model Development, Diagnostics, and
36
37 Intercomparisons (PIAMDDI) and the Pacific Northwest National Laboratories, and
38
39 benefitted from support by the National Aeronautics and Space Agency Science Mission
40
41 Directorate (WBS 281945.02.03.06.79) and the Department of Energy (DE-AC05-
42
43 76RL01830 and DE-SC0005171) as well as the Joint Research Centre of the European
44
45 Commission. We appreciate the assistance of Meridel Phillips in figure creation.
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

References

- Antle J M, Valdivia R O, Boote K, Janssen S, Jones J W, Porter C H, Rosenzweig C, Ruane A C, Thorburn P J 2015 AgMIP's transdisciplinary agricultural systems approach to regional integrated assessment of climate impacts, vulnerability, and adaptation. In Handbook of Climate Change and Agroecosystems: The Agricultural Model Intercomparison and Improvement Project (AgMIP) Integrated Crop and Economic Assessments, Part 1. C. Rosenzweig, and D. Hillel, Eds., ICP Series on Climate Change Impacts, Adaptation, and Mitigation Vol. 3. Imperial College Press, 27-44, doi:10.1142/9781783265640_0002.
- Asseng S et al 2013 Uncertainty in simulating wheat yields under climate change. *Nature Clim. Change* 3, 827-832. doi: 10.1038/NCLIMATE1916
- Asseng S et al 2015a Rising temperatures reduce global wheat production. *Nature Clim. Change*, 5(2), 143-147, doi:10.1038/nclimate2470.
- Asseng S et al 2015b Benchmark data set for wheat growth models: Field experiments and AgMIP multi-model simulations. *Open Data J. Agric. Res.*, 1, 1-5, doi:10.18174/odjar.v1i1.14746.
- Bassu S et al 2014 Do various maize crop models give the same responses to climate change factors? *Global Change Biology* 20, 2301–2320, doi: 10.1111/gcb.12520
- Blanc E 2017 Statistical emulators of maize, rice, soybean and wheat yields from global gridded crop models. *Agricultural and Forest Meteorology*, 236, 145–161. doi:10.1016/j.agrformet.2016.12.022
- Boote K J, Porter C H, Jones J W, Thorburn P J, Kersebaum K C, Hoogenboom G, White J W and Hatfield J L 2015 Sentinel Site Data for Model Improvement – Definition and Characterization. In: Hatfield, J.L., Fleisher, D. (Eds.), *Improving Modeling Tools to Assess Climate Change Effects on Crop Response*, Advances in Agricultural Systems Modeling. ASA, CSSA, and SSSA, Madison, WI, USA. doi:10.2134/advagriscystmodel7.2014.0019.
- Cammarano D et al 2016 Uncertainty of wheat water use: Simulated patterns and sensitivity to temperature and CO₂. *Field Crops Res.*, 198, 80-92, doi:10.1016/j.fcr.2016.08.015.
- Castañeda-Vera A, Leffelaar P A, Álvaro-Fuentes J, Cantero-Martínez C, Mínguez M I 2015 Selecting crop models for decision making in wheat insurance. *Europ. J. Agronomy* 68: 97-116. doi:10.1016/j.eja.2015.04.008
- Castruccio S, McInerney D J, Stein M L, Crouch F L, Jacob R L and Moyer E J 2014 Statistical Emulation of Climate Model Projections Based on Precomputed GCM Runs. *Journal of Climate* 27(5), 1829-1844.
- Challinor A J et al 2014a A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change* 4(4), 287-291. doi:10.1038/NCLIMATE2153
- Challinor A, Martre P, Asseng S, Thornton P and Ewert F 2014b Making the most of climate impacts ensembles. *Nature Climate Change* 4: 77-80.
- Challinor A, Parkes B, and Ramirez-Villegas J 2015 Crop yield response to climate change varies with cropping intensity. *Glob Change Biol*, 21: 1679–1688. doi:10.1111/gcb.12808

- 1
2
3 Clarke L et al 2014 Assessing Transformation Pathways. In: Climate Change 2014: Mitigation of Climate
4 Change. Contribution of Working Group III to the Fifth Assessment Report of the
5 Intergovernmental Panel on Climate Change [Edenhofer, O., et al. (eds.)]. Cambridge University
6 Press, Cambridge, United Kingdom and New York, NY, USA.
7
8
9 Confalonieri R et al 2016 Uncertainty in crop model predictions: What is the role of users? *Environmental*
10 *Modelling and Software* 81, 165–173.
11
12 Deryng Det al 2016 Regional disparities in the beneficial effects of rising CO₂ concentrations on crop water
13 productivity. *Nature Clim. Change*, 6, no. 8, 786-790, doi:10.1038/nclimate2995.
14
15 Durand JL et al 2017 How accurately do maize crop models simulate the interactions of atmospheric CO₂
16 concentration levels with limited water supply on water use and yield? *Eur. J. Agron.*, in press,
17 doi:10.1016/j.eja.2017.01.002.
18
19 Elliott J, Kelly D, Chryssanthacopoulos J, Glotter M, Jhunjnuwala K, Best N, Wilde M and Foster I 2014
20 The parallel system for integrating impact models and sectors (pSIMS). *Environ. Model. Softw.*,
21 62, 509-516, doi:10.1016/j.envsoft.2014.04.008.
22
23 Elliott J et al 2015 The Global Gridded Crop Model Intercomparison: Data and modeling protocols for Phase
24 1 (v1.0). *Geosci. Model Dev.*, 8, 261-277, doi:10.5194/gmd-8-261-2015.
25
26 Ewert F et al 2015 Crop modelling for integrated assessment of risk to food production from climate change.
27 *Environmental Modelling & Software* 72: 287-303
28
29 Fleisher D H et al 2016 A potato model intercomparison across varying climates and productivity levels.
30 *Global Change Biology*: 24 pp. doi: 10.1111/gcb.13411
31
32 Füssler H-M 2010 Modeling impacts and adaptation in global IAMs. *WIREs Clim Chg*, 1: 288–303.
33 doi:10.1002/wcc.40
34
35 Hartin C A, Patel P L, Schwarber A, Link R P and Bond-Lamberty B 2015 A simple object-oriented and
36 open source model for scientific and policy analyses of the global climate system - Hector v1.0.
37 *Geoscientific Model Development* 8(4):939-955. doi:10.5194/gmd-8-939-2015
38
39 Hoffmann H et al 2015 Variability of effects of spatial climate data aggregation on regional yield simulation
40 by crop models. *Climate Research* 65, 53-69.
41
42 Hoffmann H et al 2016 Impact of spatial soil and climate input data aggregation on regional Yield
43 Simulations. *PLoS ONE* 11.
44
45 Kersebaum K C et al 2015 Analysis and classification of data sets for calibration and validation of agro-
46 ecosystem models. *Environmental Modelling & Software*, 72, 402-417. DOI:
47 10.1016/j.envsoft.2015.05.009.
48
49 Kihara J et al 2015 Perspectives on climate effects on agriculture: The international efforts of AgMIP in Sub-
50 Saharan Africa. In *Handbook of Climate Change and Agroecosystems: The Agricultural Model*
51 *Intercomparison and Improvement Project (AgMIP) Integrated Crop and Economic Assessments,*
52 *Part 2.* Rosenzweig C and Hillel D, Eds., ICP Series on Climate Change Impacts, Adaptation, and
53 Mitigation Vol. 3. Imperial College Press, 3-24, doi:10.1142/9781783265640_0013.
54
55
56
57
58
59
60

- 1
2
3 Kollas C et al 2015 Crop rotation modelling—A European model intercomparison. *European Journal of*
4 *Agronomy* 70: 98-111
- 5
6 Li T et al 2015 Uncertainties in predicting rice yield by current crop models under a wide range of climatic
7 conditions. *Glob. Change Biol.*, 21, no. 3, 1328-1341, doi:10.1111/gcb.12758.
- 8
9 Liu B et al 2016 Similar negative impacts of temperature on global wheat yield estimated by three
10 independent methods. *Nature Clim. Change*, 6, no. 12, 1130-1136, doi:10.1038/nclimate3115.
- 11
12 Lobell D B, Schlenker W and Costa-Roberts J 2011 Climate trends and global crop production since 1980.
13 *Science* 333, 616–620.
- 14
15 Maiorano A et al 2017 Crop model improvement reduces the uncertainty of the response to temperature of
16 multi-model ensembles. *Field Crops Research* 202: 5-20.
- 17
18 Makowski D et al 2015 Statistical analysis of large simulated yield datasets for studying climate effects. In
19 *Handbook of Climate Change and Agroecosystems: The Agricultural Model Intercomparison and*
20 *Improvement Project (AgMIP) Integrated Crop and Economic Assessments, Part 1.* C. Rosenzweig,
21 and D. Hillel, Eds., ICP Series on Climate Change Impacts, Adaptation, and Mitigation Vol. 3.
22 Imperial College Press, 279-298, doi:10.1142/9781783265640_0011.
- 23
24
25
26 Marin F R, Thorburn P J, Nassif D S P and Costa L G 2015 Sugarcane model intercomparison: Structural
27 differences and uncertainties under climate change. *Environmental Modelling and Software*, 72,
28 372-386
- 29
30 Martre P et al 2014 Error of multimodel ensembles of wheat growth: more models are better than one. *Global*
31 *Change Biology*, 21, 911–925, doi: 10.1111/gcb.12768.
- 32
33 McDermid S P et al 2015a The AgMIP Coordinated Climate-Crop Modeling Project (C3MP): Methods and
34 protocols. In *Handbook of Climate Change and Agroecosystems: The Agricultural Model*
35 *Intercomparison and Improvement Project (AgMIP).* Rosenzweig C and Hillel D, Eds., ICP Series
36 on Climate Change Impacts, Adaptation, and Mitigation Vol. 3. Imperial College Press, 191-220,
37 doi:10.1142/9781783265640_0008.
- 38
39
40 McDermid S P et al 2015b Integrated assessments of the impacts of climate change on agriculture: An
41 overview of AgMIP regional research in South Asia. In *Handbook of Climate Change and*
42 *Agroecosystems: The Agricultural Model Intercomparison and Improvement Project (AgMIP)*
43 *Integrated Crop and Economic Assessments, Part 2.* Rosenzweig C and Hillel D, Eds., ICP Series
44 on Climate Change Impacts, Adaptation, and Mitigation Vol. 3. Imperial College Press, 201-218,
45 doi:10.1142/9781783265640_0018.
- 46
47
48
49 Meinshausen M., Raper S C B and Wigley T M L 2011 Emulating coupled atmosphere-ocean and carbon
50 cycle models with a simpler model, MAGICC6—Part 1: Model description and calibration. *Atmos*
51 *Chem Phys* 11:1417–1456
- 52
53 Mistry M, Sue Wing I, et al 2017 (article in review in same ERL special issue)
- 54
55 Moore F et al 2017 (article in review in same ERL special issue)
- 56
57
58
59
60

- 1
2
3 Mueller C and Robertson RD 2014 Projecting future crop productivity for global economic modeling, *Agric.*
4 *Econ.* 45 37–50
- 5
6 Müller C et al 2017 Global Gridded Crop Model evaluation: Benchmarking, skills, deficiencies and
7 implications. *Geosci. Model Dev.*, submitted, doi:10.5194/gmd-2016-207.
- 8
9 Nelson G C et al 2014 Climate change effects on agriculture: Economic responses to biophysical shocks,
10 *Proceedings of the National Academy of Sciences*, 111, 3274–3279, doi: 10.1073/pnas.1222465110.
- 11
12 Pirttioja N 2015 A crop model ensemble analysis of temperature and precipitation effects on wheat yield
13 across a European transect using impact response surfaces. *Climate Research* 65: 87–105.
14 doi:10.3354/cr01322
- 15
16 Portmann F T, Siebert S and Döll P 2010 MIRCA2000 – Global monthly irrigated and rainfed crop areas
17 around the year 2000: A new high-resolution data set for agricultural and hydrological modeling,
18 *Global Biogeochemical Cycles*, 24, GB 1011, doi:10.1029/2008GB003435. Ray, D.K., J.S. Gerber,
19 G.K. MacDonald, and P.C. West, 2015: Climate variation explains a third of global crop yield
20 variability, *Nat Commun*, 6, doi: 10.1038/ncomms6989.
- 21
22 Rosenzweig C et al 2013 The Agricultural Model Intercomparison and Improvement Project (AgMIP):
23 Protocols and pilot studies. *Agric. Forest Meteorol.* 170, 166–182.
24 doi:10.1016/j.agrformet.2012.09.011
- 25
26 Rosenzweig C et al 2014 Assessing agricultural risks of climate change in the 21st century in a global gridded
27 crop model intercomparison. *Proc. Natl. Acad. Sci.*, 111, 3268–3273,
28 doi:10.1073/pnas.1222463110.
- 29
30 Rosenzweig C, Jones J W, Hatfield J L, Antle J M, Ruane A C and Mutter C Z, 2015: The Agricultural
31 Model Intercomparison and Improvement Project: Phase I activities by a global community of
32 science. In *Handbook of Climate Change and Agroecosystems: The Agricultural Model
33 Intercomparison and Improvement Project (AgMIP)*. Rosenzweig C and Hillel D, Eds., ICP Series
34 on Climate Change Impacts, Adaptation, and Mitigation Vol. 3. Imperial College Press, 3–24,
35 doi:10.1142/9781783265640_0001.
- 36
37 Rosenzweig C, Antle J and Elliott J 2016 Assessing impacts of climate change on food security worldwide.
38 *Eos*, 97, no. 8, 11, doi:10.1029/2016EO047387.
- 39
40 Rosenzweig C et al 2017 Protocols for AgMIP Regional Integrated Assessments Version 7.0. available at
41 <http://www.agmip.org/regional-integrated-assessments-handbook/>
- 42
43 Rötter RP, Carter TR, Olesen JE and Porter JR 2011 Crop-climate models need an overhaul. *Nature Climate
44 Change*, 1(4): 175–177.
- 45
46 Ruane A C, McDermaid S, Rosenzweig C, Baigorria G A, Jones J W, Romero C C and Cecil L D 2014
47 Carbon–Temperature–Water change analysis for peanut production under climate change: a
48 prototype for the AgMIP Coordinated Climate-Crop Modeling Project (C3MP). *Global Change
49 Biology*, 20, 394–407, doi: 10.1111/gcb.12412
- 50
51
52
53
54
55
56
57
58
59
60

- 1
2
3 Ruane A C, Goldberg R and Chryssanthacopoulos J 2015a Climate forcing datasets for agricultural
4 modeling: Merged products for gap-filling and historical climate series estimation. *Agric. Forest*
5 *Meteorol.*, 200, 233-248, doi:10.1016/j.agrformet.2014.09.016.
6
7
8 Ruane A C, Winter J M, McDermid S P and Hudson N I 2015b AgMIP climate datasets and scenarios for
9 integrated assessment. In *Handbook of Climate Change and Agroecosystems: The Agricultural*
10 *Model Intercomparison and Improvement Project (AgMIP) Integrated Crop and Economic*
11 *Assessments, Part 1*. Rosenzweig C and Hillel D, Eds., ICP Series on Climate Change Impacts,
12 *Adaptation, and Mitigation Vol. 3*. Imperial College Press, 45-78,
13 doi:10.1142/9781783265640_0003.
14
15
16 Ruane A C et al 2016 Multi-wheat model ensemble responses to interannual climate variability. *Environ.*
17 *Model. Softw.*, 81, 86-101, doi:10.1016/j.envsoft.2016.03.008.
18
19 Singels A, Jones M, Marin F, Ruane A C and Thorburn P 2013 Predicting climate change impacts on
20 sugarcane production at sites in Australia, Brazil and South Africa using the Canegro model. *Sugar*
21 *Tech*, doi: 10.1007/s12355-013-0274-1.
22
23 van Bussel L et al 2016 Spatial sampling of weather data for regional crop yield simulations. *Agricultural*
24 *and Forest Meteorology* 220, 101-115.
25
26 Villoria N et al 2016 Rapid aggregation of global gridded crop model outputs to facilitate cross-disciplinary
27 analysis of climate change impacts in agriculture. *Environmental Modelling & Software*, 75, 193-
28 201, doi: 10.1016/j.envsoft.2015.10.016.
29
30 Wallach D, Mearns L O, Rivington M, Antle J M and Ruane A C 2015 Uncertainty in agricultural impact
31 assessment. In *Handbook of Climate Change and Agroecosystems: The Agricultural Model*
32 *Intercomparison and Improvement Project (AgMIP)*. Rosenzweig C and Hillel D, Eds., ICP Series
33 *on Climate Change Impacts, Adaptation, and Mitigation Vol. 3*. Imperial College Press, 223-260,
34 doi:10.1142/9781783265640_0009.
35
36 Wallach D, Mearns L O, Ruane A C, Rötter R P, and Asseng S 2016 Lessons from the climate modeling
37 community on the design and use of ensembles for crop modeling. *Climatic Change*, 139 (3), 551-
38 564, doi:10.1007/s10584-016-1803-1.
39
40 Warszawański L, Frieler K, Huber V, Piontek F, Serdeczny O, Schewe J (2014) The Inter-Sectoral Impact
41 Model Intercomparison Project (ISI-MIP): Project framework, *P. Natl. Acad. Sci. USA*, 111, 3228-
42 3232, doi:10.1073/pnas.1312330110.
43
44 Webber H, Zhao G, Wolf J, Britz W, Vries W D, Gaiser T, Hoffmann H and Ewert F 2015 Climate change
45 impacts on European crop yields: Do we need to consider nitrogen limitation? *European Journal of*
46 *Agronomy* 71, 123-134.
47
48 Webber H, Gaiser T, Oomen R, Teixeira E, Zhao, Wallach D, Zimmermann A and Ewert F 2016 Uncertainty
49 in future irrigation water demand and risk of crop failure for maize in Europe. *Environmental*
50 *Research Letters* 11.
51
52
53
54
55
56
57
58
59
60

- 1
2
3 Webber H et al 2017 Canopy temperature for simulation of heat stress in irrigated wheat in a semi-arid
4 environment: A multi-model comparison. *Field Crops Research* 202: 21-35.
5
6 White J W, Hoogenboom G, Kimball B A and Wall G W 2011 Methodologies for simulating impacts of
7 climate change on crop production. *Field Crops Research* 124(3):357-368. doi:
8 10.1016/j.fcr.2011.07.001.
9
10 Wiebe K et al 2015 Climate change impacts on agriculture in 2050 under a range of plausible socioeconomic
11 and emissions scenarios, *Environmental Research Letters*, 10, 085010, doi: 10.1088/1748-
12 9326/10/8/085010.
13
14 Wilby R L, Charles S, Zorita E, Timbal B, Whetton P and Mearns L 2004 Guidelines for use of climate
15 scenarios developed from statistical downscaling methods. IPCC Supporting Material, available
16 from the DDC of IPCC TG CIA.
17
18 Yin X et al 2017 Multi-model uncertainty analysis in predicting grain N for crop rotations in Europe.
19 *European Journal of Agronomy* 84: 152-165
20
21 Zhao G et al 2015 Effect of weather data aggregation on regional crop simulation for different crops,
22 production conditions, and response
23
24 Zhao G et al 2016 Evaluating the precision of eight spatial sampling schemes in estimating regional means
25 of simulated yield for two crops. *Environmental Modelling and Software* 80, 100-112.
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Tables and Figures

Table 1: Overview of multi-model, multi-site, protocol-based research activities sampling the Carbon-Temperature-Water-Nitrogen-Adaptation (CTWNA) change space by AgMIP and related projects.

Research Activity	Scope	C (ppm)	T (°C)	W (%)	N	A	Notes
AgMIP-Wheat <i>Phase 1</i>	Sites	360 to 720	-3 to +9	--	-50% to +50%	--	27 wheat models at each of four sites. #
AgMIP-Wheat <i>Phase 2a</i>	Sites	--	+0 to +16	--	--	--	30 wheat models simulated at two sites
AgMIP-Wheat <i>Phase 2b</i>	Global Network	--	+0 to +4	--	--	--	30 wheat models at 30 well-watered sites.
AgMIP-Wheat <i>Phase 3</i>	Global Network	360 to 550	+0 to +4	--	--	--	32 wheat models at 60 sites (water-limited and well-watered sites).
AgMIP-Maize <i>Phase 1</i>	Sites	360 to 720	-3 to +9	--	--	--	23 maize models at each of 4 sites
AgMIP-Maize <i>Phase 2</i>	Sites	387 and 550	--	RF and Irr.	--	--	21 maize models for Braunschweig, Germany, FACE site
AgMIP-Rice <i>Phase 1</i>	Sites	360 to 720	-3 to +9	--	varied N	--	13 rice models at each of 4 sites. Two sites included N treatments ranging from 30-150 kg N/ha
AgMIP-Rice <i>Phase 2</i>	Sites	360 to 720	--	--	varied N	--	16 rice models at each of 2 FACE sites (Japan and China).**
AgMIP-Potato	Sites	360 to 720	-3 to +9	-30 to +30	--	--	9 potato models at each of 4 sites
AgMIP-Canola	Sites	360 to 720	-3 to +9	-25 to +25	0% to 150% of obs	--	8 canola models at each of 7 sites
AgMIP-Sugarcane	Sites	350 to 750	-3 to +9	-30 to +30	--	--	2 sugarcane models at 7 Brazilian sites.
AgMIP-Livestock and Grasslands <i>Phase 2</i>	Sites	330 to 900	-1 to +8	-50 to +50	--	--	Common protocols for single model tests at 14 sites. 7 models contributed yield and GHG balance results.
AgMIP Regional Integrated Assessments	Sites	360 to 720	-2 to +8	-75 to +100	0 to 210	--	2 models each for 10 sites, multiple crops at many of the sites.

					kg N/ha		
C3MP	Global Network	330 to 900	-1 to +8	-50 to +50	--	--	1137 simulation sets in 56 countries; 18 crop species, 23 crop models
MACSUR-IRS Phase 1	Sites	--	-2 to +9	-50 to +50	--	--	26 wheat models at 4 sites in Europe.
MACSUR - Crop Rotation	Sites	374 and 550	--	--	100% and 50% of obs	--	15 models with and without crop rotations. CN sensitivity tests performed at Brauns weig, Germany, and N sensitivity at Thibie, France.
GGCMI-Phase 2	Global Grid	360 to 810	-1 to +6	-50 to +30 plus irrigated	10 to 200 kg N/ha	Fully reverse accelerated maturity	12 participating models. ** Includes no water stress test and no nitrogen stress test. Adaptation adjusts cultivars to maintain planting to maturity duration.

*Notes: RF=Rainfed; Irr.=Irrigated; GHG=Greenhouse Gas; variedN = multiple nitrogen treatments at each site; #= Nitrogen tests were only performed for 20 wheat models containing nitrogen dynamics; ** = ongoing project, final participation may change.*

Table 2: AgMIP-Wheat, AgMIP-Maize, and AgMIP-Rice Team Phase descriptions.

Phase (and key references)	Description
AgMIP-Wheat	
Phase 1 (Asseng et al., 2013; Martre et al., 2015)	Protocol-based multi-model intercomparison at diverse, high-quality sites. Included limited information and full information calibration settings.
Phase 2a (Asseng et al., 2015a)	Protocol-based multi-model analysis of temperature response at Hot Serial Cereals artificial heating experiment in Arizona and temperature responses in Mexico.
Phase 2b (Asseng et al., 2015a; Liu et al., 2016)	Intercomparison of temperature responses across 30 sites selected as a representative network of well-watered wheat production regions around the world.
Phase 3	Intercomparison of temperature responses across 60 sites selected to represent both well-watered and water-limited wheat production regions around the world.
AgMIP-Maize	
Phase 1 (Bassu et al., 2014)	Protocol-based multi-model intercomparison at diverse, high-quality sites. Included limited information and full information calibration settings.
Phase 2 (Durand et al., 2017)	Protocol-based multi-model intercomparison at Free-Air Carbon Enrichment (FACE) site in Germany.
AgMIP-Rice	
AgMIP-Rice Phase 1 (Li et al., 2015)	Protocol-based multi-model intercomparison at diverse, high-quality sites. Included limited information and full information calibration settings.
AgMIP-Rice Phase 2	Protocol-based multi-model intercomparison at FACE Sites in Japan and China.

Table 3: Overview of GGCM phases and model participation.

Phase (and key references)	Description [and # of models participating]
Fast Track Rapid Assessment (<i>Rosenzweig et al., 2014</i>)	Conducted for AgMIP/ISIMIP using default versions of global gridded crop models, historical period and future scenarios from downscaled GCMs. Simulated maize, wheat, rice and soybean [7 GGCMs]
Phase 1 Historical Intercomparison (<i>Elliott et al., 2015</i> ; <i>Müller et al., 2017</i>)	Default, harmonized, and No Nitrogen Stress versions of gridded crop models run over historical period using up to 9 climate forcing datasets. Simulated maize, wheat, rice and soybean [15 GGCMs]
Phase 2 CTWNA Sensitivity [results submitted 2016-17]	Default simulations for historical period and sensitivity tests for [CO ₂], temperature, water, nitrogen, and adaptation for all grid cells and crops. Simulated maize, spring wheat, winter wheat, rice and soybean [~12 GGCMs]
Phase 3 Future Assessment [planned for 2017-18]	Conducted for AgMIP/ISIMIP to assess future agricultural production under climate change scenarios. [~12-20 GGCMs anticipated]

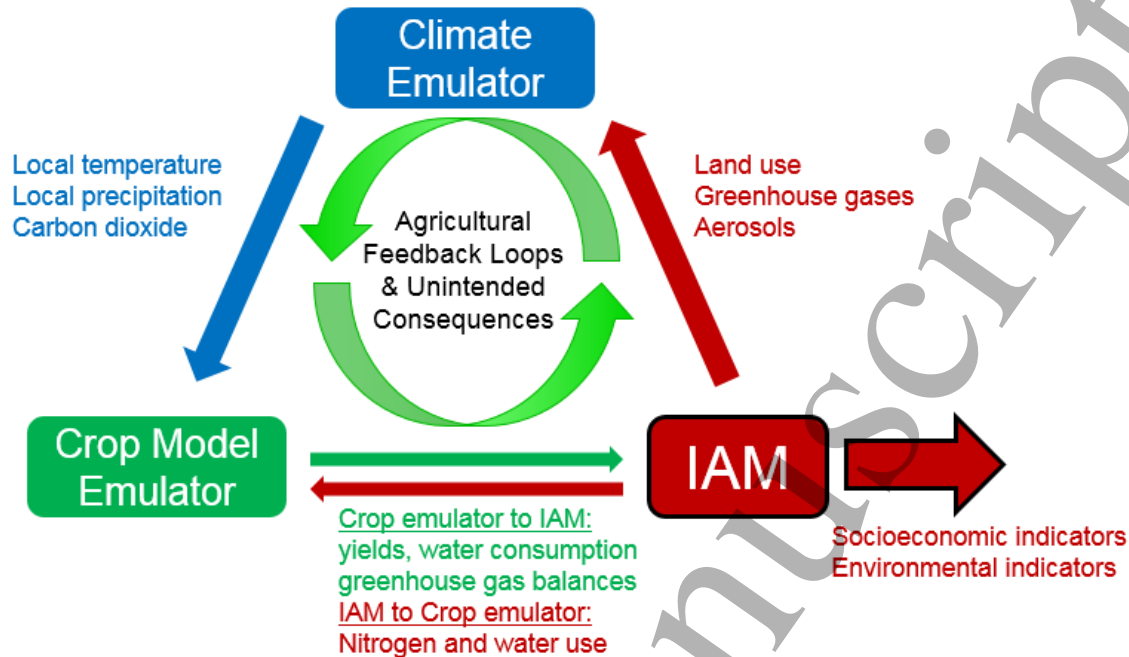


Figure 1: Overview of aspirational framework and agricultural applications for IAM with linked climate and crop model emulators. IAMs typically focus on the interplay of socioeconomic development and environmental outcomes, however inclusion of the climate and crop model emulation pathway allows for the resolution of agricultural feedback loops and unintended consequences across scales and sectors. Note that climate emulators have additional applications within IAMs beyond the agricultural sector illustrated here.

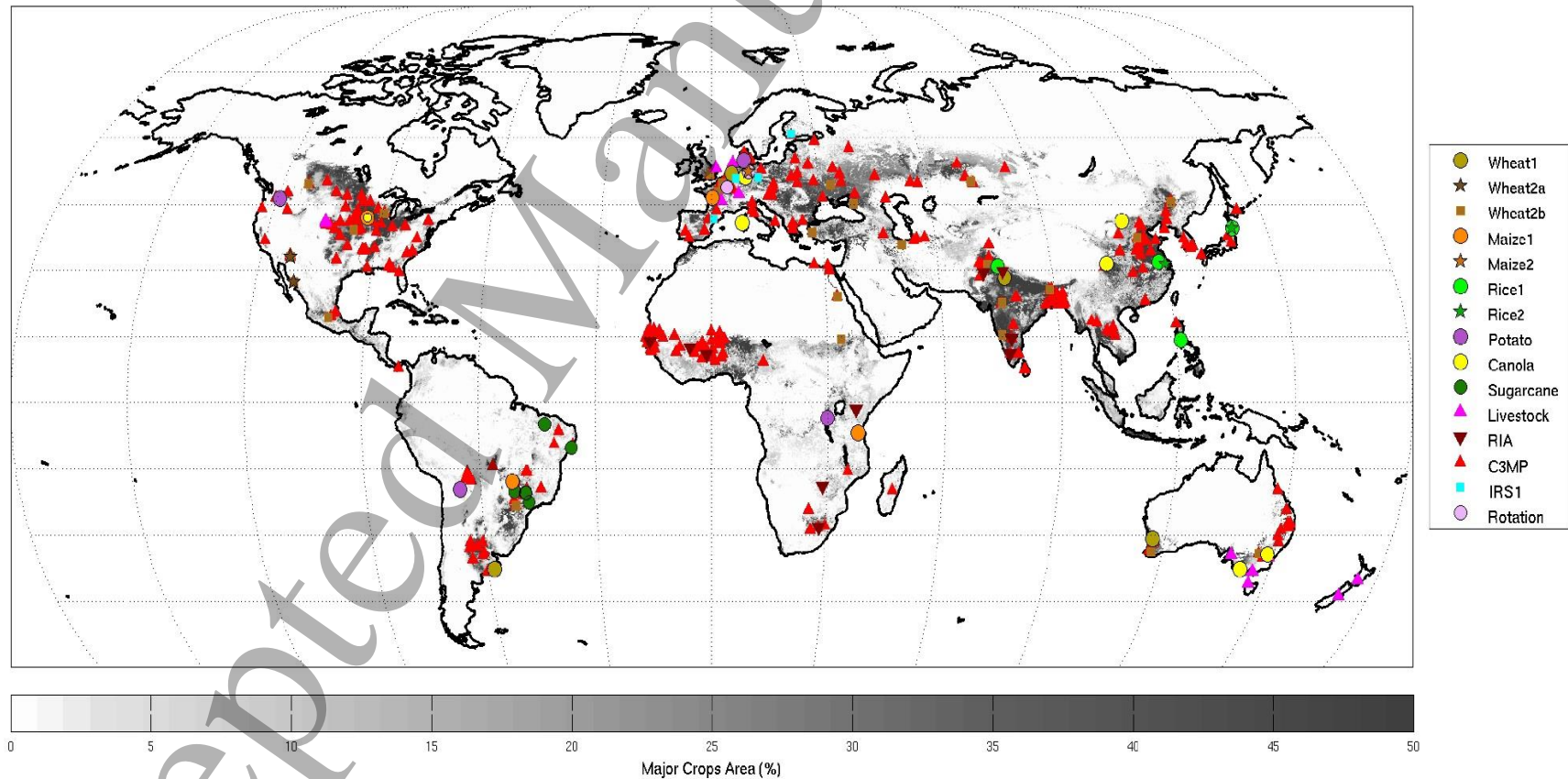


Figure 2: Map of sites and networks for agricultural impacts studies exploring responses to [CO₂], temperature, water, nitrogen, and/or adaptation, and major crops area (%) by Monfreda et al. (2007); note that studies cover many major production regions, while GGCMI activities simulate the entire land surface.

Comment citer ce document :

32

Ruane, A. C., Rosenzweig, Asseng, S., Boote, Elliott, J., Ewert, F., Jones, Martre, P.,
McDermid, S. P., Müller, C., Snyder, A., Thorburn, P. J. (2017). An AgMIP framework for improved
agricultural representation in integrated assessment models. Environmental Research Letters, 12.

DOI : 10.1088/1748-9326/aa8da6

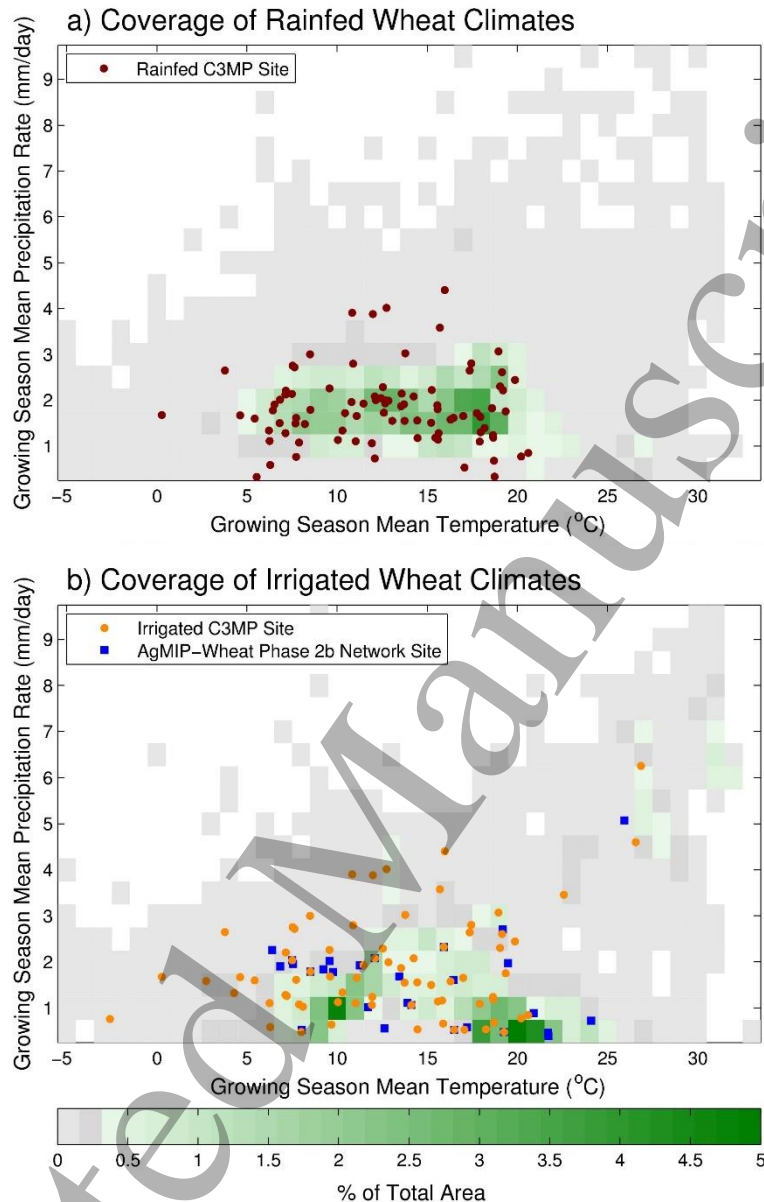


Figure 3: Distribution of global (a) rainfed and (b) irrigated wheat area displayed according to growing season mean temperature and precipitation rate (from MIRCA observations, Portmann et al., 2010). Corresponding C3MP and AgMIP-Wheat Phase 2b network sites are presented to show coverage of global wheat-cropping systems. Note that the AgMIP-Wheat 2b network consists entirely of well-watered sites including both irrigated croplands and rainfed areas that rarely experience water stress.

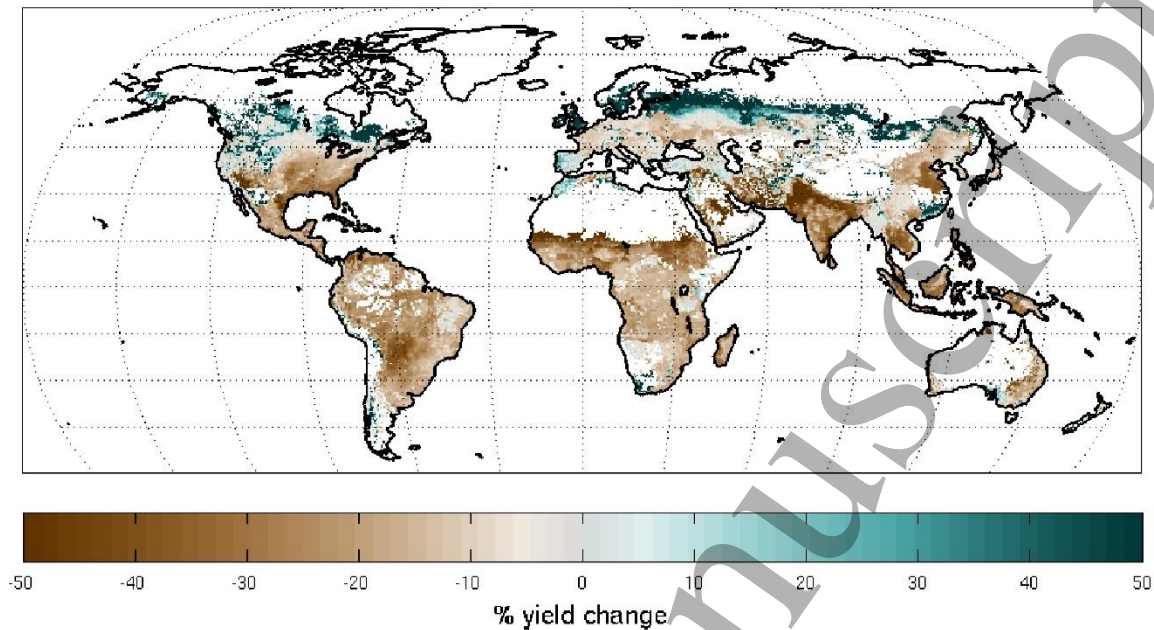


Figure 4: Example of regional differences in climate response. pDSSAT rainfed maize yield change (%) to a hypothetical 150ppm increase in [CO₂] and a 2 °C rise in temperature from GGCM Phase 2 (all regions grown with 200 kg N/ha with no adaptation to isolate climate response).



Figure 5: Wheat growing seasons (average planting and harvest date) at each well-watered site in the AgMIP-Wheat network as well as corresponding grid cells in the harmonized GGCMi protocols. Differences for Canada, Turkey, and Ukraine indicate that GGCMi considered spring wheat while the wheat network considered winter wheat, while India and Mexico reflect that there are two wheat-growing seasons in these regions.

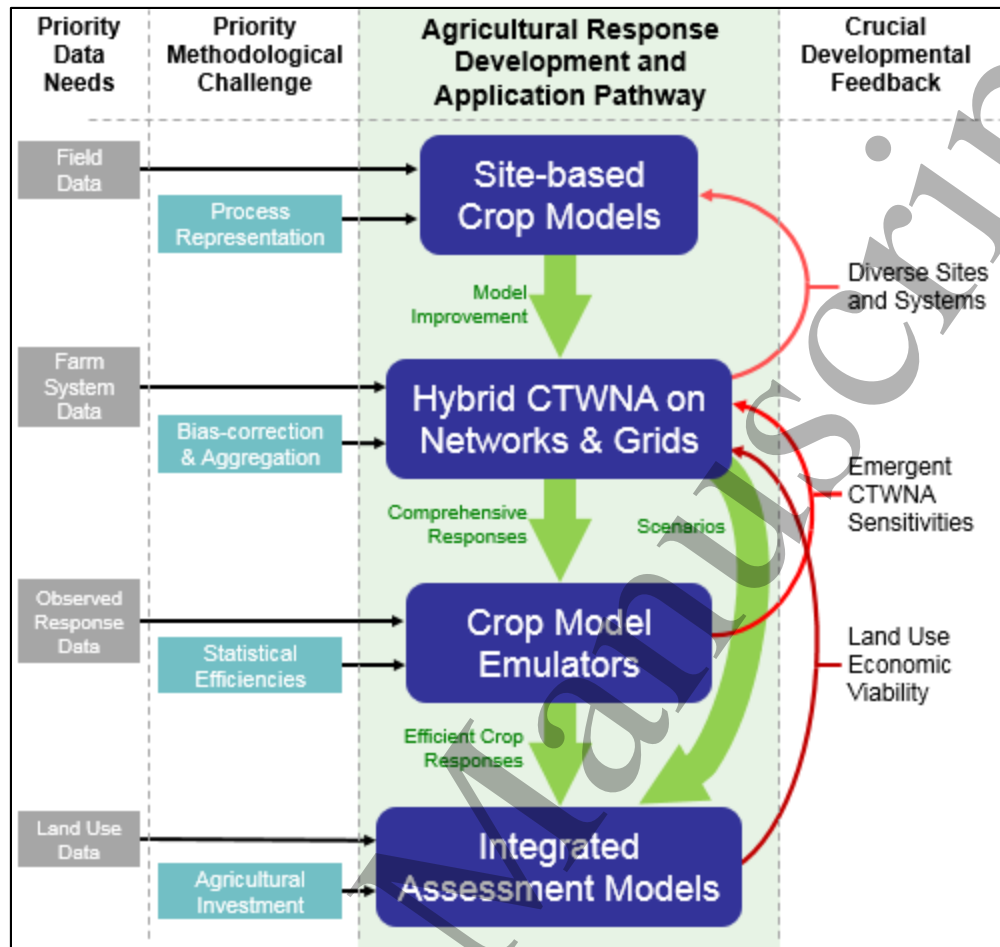


Figure 6: AgMIP framework for improved agricultural representation in IAMs. The core agricultural response development and application pathway (green arrows) spans several levels of model applications (dark blue boxes) and recognizes that site-based crop models are the backbone of model networks and grids, which feed into IAMs either directly or through crop model emulators built upon a hybrid system blending network and gridded CTWNA responses. Improvement in each level of model development requires access to data for evaluation and configuration (gray boxes) as well as methodological advances (light blue boxes). Agricultural applications also inform development up the framework chain, with IAMs providing critical information about the economic viability of changing land use patterns, emulators helping to isolate aggregate CTWNA responses, and networks and grids testing site-based models in more diverse settings.