Imperfect Forecasts and Decision Making in Agriculture

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Abstract

The past few decades saw tremendous advances in weather and climate forecasting ability. These advances opened up the possibility of strategic adaptation of agricultural management in anticipation of weather and climate outcomes, resulting in a profusion of studies estimating the value of weather and climate forecasts. Estimated values from this literature were, in many cases, substantive, implying that farmers could significantly benefit from forecasts. Yet the

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8 response from farmers, it appears, was not commensurate with the values sug-
9 gested by the studies. In this article we make the case that forecast quality,
10 both real and perceived, may still pose a significant obstacle; despite recent
11 gains in forecasting ability, forecasts—especially seasonal climate forecasts—
12 are far from certain. Unless this uncertainty is explicitly and more realistically
13 incorporated into models of forecast use, a gap will always exist between ex-
14 pectations of forecast use and actual forecast use by farmers. We conclude by
15 establishing the need for 1) making imperfect forecasts a standard feature in
16 models of forecast use and 2) informing these models with empirical research
17 on farmer use of imperfect forecasts.

18
19 **KEYWORDS:** forecast accuracy, weather, climate, agricultural decision making,
20 imperfect information

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1 Introduction

Agricultural production is subject to much uncertainty, a large part of which stems from day-to-day weather variability, and seasonal variability linked to inter-annual climate fluctuations. In theory, the availability of better weather and climate forecasts should improve the economic welfare of growers, whether through increased revenue and/or reduced volatility in revenue. As climate change increases both the variability and uncertainty of weather and climate patterns, the value of forecasts to growers should also increase. Under an ideal management scenario, growers should rapidly and fully assimilate improved forecasts into their crop management decisions.

This assertion is based on a large body of studies that model producer decisions (and corresponding returns) in response to forecasts. In these models, given a forecast, a regionally-representative farmer chooses the management alternative that he/she expects will yield the greatest return.¹ The value of a forecast source is the average difference between the resultant stream of returns and that which would result in its absence. A meta-analysis of such studies by Mjelde, Hill, and Griffiths (1998) places the value of forecasts to US agriculture between \$0/acre and \$3.40/acre. For a relatively recent, comprehensive review of value-of-seasonal-forecast studies, please see Meza, Hansen, and Osgood (2008).

In reality, reliance on improved weather and climate forecasts is limited and not

¹Examples of commonly modeled management alternatives are crop choice, varietal choice, planting dates, input application rates and input timing.

47 commensurate with the estimated benefits of doing so. This is especially true of
48 longer-term climate information, in contrast to daily or weekly weather forecasts. For
49 a novel source of weather information to have any real marginal value, it must lead to
50 changes in management choices that result in improved outcomes. Clearly, many fac-
51 tors stand between information availability and information use. Limited reliance on
52 new information sources can be a function of multiple factors, including the following:
53 grower objectives and risk preferences, enrollment in risk-management programs (e.g.
54 crop insurance), the inability (financial, physical, or perceived) of changing practices
55 in response to forecasts, the format and quality of the forecasts themselves, and the
56 process by which decision makers assimilate these forecasts (Sonka et al. 1987; Ar-
57 tikov et al. 2006; Cabrera, Letson, and Podestá 2007; Klockow, McPherson, and
58 Sutter 2010; Carriquiry and Osgood 2012). However, the observation that farmers
59 are less responsive to longer-term weather and climate forecasts—combined with the
60 fact that forecasts with longer lead times are generally of lower quality—implies that
61 forecast quality may be a critical factor.

62 This review focuses on the quality (or uncertainty) of forecasts. First, it pro-
63 vides a general sense of the current quality of forecasts. Second, it summarizes the
64 main modeling approaches used to depict forecast quality in value-of-seasonal-forecast
65 studies to date. Here we find that, while some models of seasonal forecast use allow
66 for imperfect forecasts, they are not nearly as numerous as the ones that assume
67 perfect forecasts. Moreover, the modeling of the assimilation process for imperfect

68 forecasts appears to be somewhat *ad hoc* and driven entirely by theory, rather than
69 any empirical tests or observations. Third, this study provides a simple example of a
70 typical model and uses the results of this example to explain the commonly reported
71 observation of many farmers ‘paying attention’ to forecasts while, at the same time,
72 not ‘using’ them. This simple model suggests the existence of a critical ‘minimum
73 accuracy threshold’ that forecasts must surpass in order to be of any practical use.
74 We conclude by establishing the need for i) making uncertainty a standard feature
75 of forecast-use-(and-value) models and ii) improving communication with extension
76 agents and farmers themselves so that basic model assumptions can be vetted and
77 refined.

78 **2 The current state of weather and climate fore-** 79 **casts**

80 Over the past two decades, the meteorological and climate community has made
81 steady progress in the accuracy and lead-time of weather and climate forecasts. Yet
82 despite these gains, forecast quality (real and perceived) may still be the primary
83 limitation in forecast use (Hu et al. 2006). In this section we discuss the availability,
84 actual quality, and perceived quality of weather and climate forecasts.

2.1 Forecast availability

Some of the most common sources of forecasts in the U.S. include products developed by two entities within the National Oceanic and Atmospheric Administration (NOAA): the National Weather Service (NWS) and the Climate Prediction Center (CPC). Both the NWS and CPC provide interactive, on-line, map-based forecast products. For example, on the NWS website (www.weather.gov), users can select any point on a U.S. map and obtain location-specific forecasts, including maximum and minimum temperatures and precipitation, for the next seven days. Users can also view maps of precipitation forecasts extending up to five days ahead, and hazardous weather outlooks extending up to three days. The CPC website (www.cpc.ncep.noaa.gov) provides 6-to-10-day, 8-to-14-day, monthly, and seasonal outlooks. These forecasts are also presented as color-coded maps showing the probability of above or below-normal occurrences. It also presents a ‘Weekly Weather and Crop Bulletin,’ a joint publication by NOAA and USDA. Additionally, the two websites provide contextual information for their forecasts, which may be useful to the more weather- and climate-attuned users, and informative for average users as well.

In addition to forecasts disseminated via the NWS and CPC, NOAA provides current-state reports on Pacific Ocean sea surface temperature, as well as outlooks related to El Niño and La Niña events. These are helpful for weather- and climate-attuned farmers in the regions affected by El Niño and La Niña. NOAA also offers

seasonal drought outlooks. Finally, an additional source for forecasts covering North America is the European Center for Medium Range Weather Forecasts (ECMWF). Forecasts from these sources are based on models that incorporate the physics and chemistry of the atmosphere, as well as modulation by land surface and oceans. Monthly and seasonal forecasts are the statistical predictions of such models. The scientific background of these forecasts, models, and resultant products are extensively documented in the published literature (For the most recent examples, please see Baars and Mass (2005), McEnery et al. (2005), Saha et al. (2006), Yussouf and Stensrud (2006), Ebert, Janowiak, and Kidd (2007), O’Lenic et al. (2008), Ruth et al. (2009), Stensrud et al. (2009), Charba and Samplatsky (2011), and Magnusson and Källén (2013)).

Anecdotally, farmers increasingly report using other sources of weather and climate forecasts such as AccuWeather, The Weather Channel, and The Climate Corporation. At this point in time, these sources generate forecasts by aggregating weather and climate data from existing networks maintained by the federal, state, and local governments, as well as private citizens. The main drawback associated with data from such sources is that they are typically collected by a diverse set of instruments. When a single network uses instruments that produce data of differing quality—due to differences in manufacturer, model, measurement methodology, maintenance schedules and/or exposure²—the quality of data produced by the entire network can no

²Instrumentation exposure is affected by the presence of manmade or natural objects near the observing equipment. For example, if there is a large tree close to wind and precipitation measuring

126 longer be gauged. In other words, inhomogeneity of instruments within a meteoro-
127 logical network renders the quality of its forecasts ‘unknowable.’

128 **2.2 Forecast quality**

129 The quality of a forecasts depends on many factors. As one would expect, forecasts
130 with longer lead times (i.e. forecasts of conditions that are farther in the future) are
131 generally less accurate than those with shorter lead times. In general, precipitation
132 forecasts are less accurate than temperature forecasts. And, by construction, forecasts
133 of lower resolution (e.g. those that predict the likelihood of three categorical events—
134 above average, average, and below average temperatures) are more accurate than
135 those of higher resolution (e.g. those that predict the likelihood of events across five
136 categories).

137 The quality of forecasts can be described using many, inter-related, general met-
138 rics such as accuracy, skill, reliability, sharpness, resolution, and uncertainty (Stanski,
139 Wilson, and Burrows 1989). Of the myriad measures used to quantify these charac-
140 teristics, here we discuss two: the *post agreement rate* and the *hit rate*. These are both
141 measures of accuracy and the two most commonly used parameters to convey forecast
142 uncertainty in forecast use models. Moreover, accuracy measures for select forecast

instruments, the tree will obstruct the natural flow of wind, causing inaccuracies in wind speed and
direction measurements. As another example, a temperature sensor located close to a building or
an asphalt road would record higher temperature than actual air temperatures, introducing bias
(Mahmood, Foster, and Logan 2006; Pielke Sr. et al. 2007).

sources—most notably the Climate Prediction Center—are available to the lay user in terms of *post-agreement rates*. It is important to note that these two measures are germane to deterministic, categorical forecasts. With deterministic, categorical forecasts, the predictands themselves are discrete, mutually exclusive, and not qualified with measures of uncertainty.³ An example of such a forecast is ‘It will be an El Niño year.’

The simplest way to think about uncertainty is by considering historical data on both forecasts and outcomes. Each observation can be categorized by what was forecast and what actually occurred. Using ENSO phase forecasts as our example, all observations (or years, given our example) over a sample period can be organized into a contingency table such as the one below, with a through i being the number of observations falling into each category.

	outcome=El Niño	outcome=Neutral	outcome=La Niña
forecast= El Niño	a	b	c
forecast= Neutral	d	e	f
forecast = La Niña	g	h	i

Post-agreement rates pertain to forecasts; for an El Niño forecast, it is defined as follows:

³These forecasts comprise one narrow class of forecasts among many; however, focusing on this particular forecast type permits the simplest explanation of our concepts.

$$\begin{aligned}
\text{post-agreement rate, forecast=El Niño} &= \frac{\text{correct El Niño forecasts}}{\text{all El Niño forecasts}} \\
&= \frac{a}{a + b + c}
\end{aligned}$$

158 In contrast, *hit rates*, or *probabilities of detection*, pertain to outcomes. For an El
159 Niño outcome,

$$\begin{aligned}
\text{hit rate, outcome=El Niño} &= \frac{\text{correct El Niño forecasts}}{\text{all El Niño outcomes}} \\
&= \frac{a}{a + d + g}.
\end{aligned}$$

160 There is, of course, more to measuring forecast quality than simply comparing
161 forecasts to outcomes, *ex post*. Widely used to determine the (*ex ante*) uncertainty
162 of a particular forecast is an *ensemble forecast*, or a set of closely related forecasts
163 (ensemble members). Recall that forecasts take current (initial) conditions and use
164 models to predict their evolution over time. Since atmospheric processes are complex,
165 a small degree of uncertainty in the initial condition may become large at the end
166 of a forecast period. There is also uncertainty regarding the model itself. Therefore,
167 an ensemble forecast is produced by running multiple models with slightly different
168 initial conditions and/or model parameters. If all ensemble members nonetheless
169 predict similar outcomes, then a high degree of confidence is placed on a forecast for
170 that outcome. It is worth noting that even probabilities forecasted using ensemble
171 forecasts are typically verified against historical event probabilities. For a discussion

172 on the advantages and caveats of ensemble forecasts, please see Kharin and Zwiers
173 (2002). Interestingly, when forecast users consult multiple sources, they are, in effect,
174 generating their own ‘ensemble forecast.’ Intuitively, here too, consistency among the
175 sources should signal a higher degree of certainty surrounding a particular forecast.⁴

176 It is difficult to find published literature that neatly summarizes the current state
177 of forecast quality. Studies that discuss forecast quality are generally inaccessible
178 to the lay reader, in part, because of the many different measures, the wide variety
179 of forecast types, and the many model and initial condition factors considered. In
180 general, however, the quality of forecasts has improved, especially so for precipitation.
181 For example, recent work suggests that the accuracy of long-range climate forecasts
182 by the CPC for temperature and precipitation forecasts—measured using the Heidke
183 Skill Score⁵—have improved approximately 18% and 195%, respectively (O’Lenic
184 et al. 2008).

185 The Climate Prediction Center’s website is unique in that it presents forecasts in
186 explicitly probabilistic format.⁶ Regions are designated with percent probabilities—in
187 this case, *post-agreement rates*⁷—of experiencing ‘above average,’ ‘below average,’ and

⁴We thank our anonymous reviewer for this observation.

⁵*Skill* is a measure the accuracy of forecasts relative to a reference standard, typically random forecasts based on historical event probabilities. In this sense, they convey the informativeness of the forecasts.

⁶We intentionally avoid calling forecasts in probabilistic format ‘probabilistic forecasts’ since this connotes how forecasts are generated (e.g. ensemble forecasts), rather than how they are presented to users.

⁷Note that the practical interpretation of a post-agreement rate (hit rate) remains the same

188 ‘average’ temperatures (precipitation). For 6-to-8 day temperature forecasts, these
189 percentages typically range from 33% (climatological average, by definition) to 80%,
190 meaning that, at least for some regions, higher (lower)-than-average temperatures
191 can be predicted with considerable certainty. On the other hand, for three-month
192 precipitation outlooks, even the highest probabilities rarely exceed 50%, meaning that
193 such forecasts are only slightly more informative than the historical average. Taking
194 these accuracy levels as an indication of the general quality of forecasts, forecasts are
195 indeed still far from perfect.

196 **2.3 Perceptions of forecast quality**

197 Perceptions of forecast quality can matter as much as—if not more than—actual
198 forecast quality since, ultimately, it is the farmers’ perceptions of forecast quality
199 that drive forecast use. Hu et al. (2006) note, “The fact that the features of forecasts
200 *have changed* over time but that the use of forecasts by farmers *has not changed*
201 suggests the need to focus on the internal factors and reevaluate the forecast use
202 and influence from the perspective of farmers, asking the questions concerning not
203 only how farmers perceive forecasts, but also how farmers value those perceptions (p.
204 1191).”

205 The question of how ‘reliable’ farmers find forecasts has been studied primarily via
206 structured interviews and focus groups (e.g. Changnon (2004), Artikov et al. (2006),
regardless of *how* it is generated—be it from the historical record or, more commonly, ensemble
forecasts.

Crane et al. (2010), Mehta et al. (2013)). Artikov et al. (2006) find that ‘attitude’ is among the strongest determinants of farmers’ likelihood to use weather forecasts. Crucially, their ‘attitude’ variable is composed of a ‘belief’ component which the authors generate by asking participants how likely they find weather forecasts to be of use in meeting particular goals, such as conserving water and choosing the best crops and varieties. Crane et al. (2010) conduct ethnographic interviews with 38 farmers in Southern Georgia and summarize, “Although farmers are highly attuned to weather forecasts, their use of such information is hindered by doubts about the information’s relevance and accuracy (p. 52).” In particular, the authors find that farmers are less likely to rely on forecasts with greater lead times and, as a result, rarely seek out seasonal climate forecasts. They also note that the majority of interviewed farmers gauge a forecast source’s reliability based on personal experience (i.e. how well the forecasts matched up with personally observed outcomes). Similarly, Mehta et al. (2013) report that, although Missouri River Basin farmers are eager for decadal climate outlooks, the ‘credibility’ of these outlooks remains a primary obstacle to their use. Finally, through a unique long-term study (1981-2001) of climate prediction usage by U.S. agribusinesses, Changnon (2004) shows that, while improvements in availability, accuracy, and lead-time have contributed to increased reliance on climate forecasts over the 21-year period, a perception of low accuracy still keeps many participants from relying on these predictions.

The above studies suggest that perceived forecast quality is an important de-

228 terminant of forecast access, that perceived forecast quality is based primarily on
229 personal experience, and that longer-term weather forecasts and seasonal forecasts
230 are oftentimes still considered too ‘unreliable’ to be of any practical use to farmers.
231 In short, perceptions matter and, currently, many types of forecasts are perceived
232 as being too unreliable. However, given the current (actual) quality of seasonal and
233 other longer-term forecasts, these perceptions may be reasonable and—for all practical
234 purposes—correct. As we demonstrate using an example model in section 4, the
235 decision to not rely on forecasts may be a rational one, given the current accuracy
236 levels of many types of forecasts.

237 **3 The depiction of forecast uncertainty in models** 238 **of forecast use**

239 Despite the consensus that the accuracy of mid- to long-range forecasts is nowhere
240 near perfect, only a relatively small portion of value-of-forecast studies incorporates
241 forecast uncertainty. For example, in Meza, Hansen, and Osgood’s (2008) extensive
242 review of applied value-of-seasonal-climate-forecasts studies, the authors identify only
243 a handful that incorporate imperfect forecasts.⁸ In this section we present a brief
244 discussion on the modeling of perfect forecasts, followed by a more extensive discussion
245 of the modeling of imperfect forecasts.

⁸Granted, the focus of such studies is typically something else, such as risk aversion or prices; for these studies, perfect forecasts is likely a simplifying assumption.

246 Unlike imperfect forecasts, the definition of a perfect forecast is widely agreed
247 upon. In the case of deterministic, categorical forecasts, it is information that iden-
248 tifies a single event that takes place with certainty. If we think of a single forecast
249 as a signal describing a distribution of probabilities over all of the potential outcome
250 events, then the distribution associated with a perfect forecast is a degenerate distri-
251 bution with all of its mass at the particular event being forecast. All predictions are
252 realized and, equivalently, all outcomes are correctly predicted.

253 The typical perfect-forecast study asks, ‘given the historical climate/weather record,
254 what would have been the best management practice(s) for each season?’ It then
255 calculates the profit stream that would have resulted from using the optimal manage-
256 ment practice(s) each season and compares it to that which would have resulted from
257 implementing the static optimal management practice(s). Three examples of such
258 studies are Jones et al. (2000), Hansen et al. (2001), and Messina, Hansen, and Hall
259 (1999). From a decision modeling standpoint, this is equivalent to assuming that the
260 decision maker i) receives perfect forecasts and ii) perfectly adopts the transmitted
261 signal—that is, the decision maker’s personal, post-forecast probability distribution
262 of events (i.e. her *posterior* distribution) is identical to the one that was forecasted.
263 This second assumption of perfect adoption is reasonable given the assumption of
264 perfect forecasts; if the forecasts are never wrong, why should the decision maker act
265 as if otherwise? Thus, within the class of studies that assume perfect forecasts, there
266 is consistency in the definition of a forecast and the process by which it is assimilated

267 by the decision maker; in the presence of perfect forecasts, the decision maker simply
 268 ‘knows’ *ex ante* what the outcome will be, and takes the action that would generate
 269 the most profit or utility.

270 Once studies allow for imperfect forecasts, they begin to diverge in their modeling
 271 approaches. However, the literature shows two basic approaches: i) incorporating the
 272 uncertainty into the decision maker’s posterior distribution and ii) incorporating it
 273 into the decision maker’s belief, or likelihood matrix, and then assuming Bayesian
 274 updating. As will become clear, the two modeling approaches are closely related to
 275 each other.⁹

276 Continuing our example of the three ENSO phases, the following 3×3 matrix
 277 gives the probabilities that the decision maker places on each outcome (in the rows),
 278 given particular forecasts (in the columns). This is a posterior matrix; it gives all of
 279 the probabilities that the decision maker places on each event taking place, condi-
 280 tional on the forecasts.

	forecast=El Niño	forecast=Neutral	forecast=La Niña
281 outcome= El Niño	$p(E E)$	$p(E N)$	$p(E L)$
outcome= Neutral	$p(N E)$	$p(N N)$	$p(N L)$
282 outcome= La Niña	$p(L E)$	$p(L N)$	$p(L L)$

283 One way to model imperfect forecasts is to build the uncertainty directly into the

⁹These approaches are also consistent with the framework and behavioral assumptions used in *cost-loss* analyses. We do not discuss cost-loss analyses of forecast quality any further in this paper except to refer the reader to Zhu et al. (2002) and Palmer (2002) for examples.

284 above matrix, by assigning the diagonal elements of the matrix values of less than
 285 one, and the off-diagonal elements values greater than zero. This is the approach
 286 taken by Katz, Brown, and Murphy (1987), Sonka et al. (1987), Mjelde et al. (1993),
 287 Mjelde, Hill, and Griffiths (1998) and Adams et al. (2003). If forecasts are categorical
 288 and presented in non-probabilistic format, as in our example, the diagonal elements
 289 are equivalent to the *post-agreement rates* (PAR) of the forecasts. For example, Sonka
 290 et al. (1987) vary the PAR from 1 (perfect forecasts) to 0.72 for three categories of
 291 growing conditions for three decision stages and varying lead times for corn producers
 292 in east central Illinois. Using the same setting, Mjelde, Hill, and Griffiths (1998) vary
 293 the PAR between 1 and 0.44 for five categories of growing conditions at eight deci-
 294 sion junctures throughout the growing season. Adams et al. (2003) consider PARs
 295 of 1 and 0.7 for three ENSO states (El Niño, La Niña, and Neutral) across several
 296 Mexican states. Using a slightly different approach, Meza and Wilks (2003) predict
 297 three-month ahead ENSO states from sea surface temperatures for Chilean rain-fed
 298 agriculture. They use both a discrete Markov process and an autoregressive process;
 299 the discrete Markov process has PARs of approximately 0.6 for El Niño and La Niña
 300 states.

301 Other studies go back one step further and explicitly model the belief-updating
 302 process—that is, the process of a decisionmaker using forecasts to update her prior
 303 distribution to then arrive at her posterior distribution (e.g. Solow et al. (1998),
 304 Adams et al. (1995)). Here, the posterior distribution is a function of two things: the

305 ‘likelihood’ matrix and the prior distribution. It is assumed that the decision maker
 306 uses Bayesian updating. Given a particular forecast k , the probability of event n
 307 taking place (i.e. the outcome being n conditional on having received the forecast k)
 308 is

$$p(o = n|f = k) = \frac{\pi(f = k|o = n)h(o = n)}{\sum_N \pi(f = k|o = n)h(o = n)}$$

309 where $\pi(f = k|o = n)$ denotes the probability of receiving forecast k conditional
 310 on the outcome n and $h(o = n)$ is the absolute probability of event n (i.e. the
 311 prior). Using our ENSO-phase example above, the decision-maker’s belief about
 312 the probability of the outcome being, say, El Niño conditional on having received the
 313 forecast ‘El Niño’ ($p(o = \text{El Niño}|f = \text{El Niño})$) is a function of the absolute likelihood
 314 of an El Niño outcome ($h(o = \text{El Niño})$), her perception of how frequently the signal
 315 matches the true outcome ($\pi(f = \text{El Niño}|o = \text{El Niño})$), and the absolute likelihood
 316 of an El Niño forecast ($\sum_{n=E,N,L} \pi(f = \text{El Niño}|o = n)h(o = n)$). Arranging all of
 317 the resultant posterior probabilities in a single matrix, we arrive at the same N -by- K
 318 matrix as above.

319 If we take the user’s perceptions of how frequently forecasts match the outcomes
 320 ($\pi(f = k|o = n)$) and arrange these in a matrix, we have the K -by- N *likelihood ma-*
 321 *trix*:

	outcome=El Niño	outcome=Neutral	outcome=La Niña
322 forecast= El Niño	$\pi(E E)$	$\pi(E N)$	$\pi(E L)$
forecast= Neutral	$\pi(N E)$	$\pi(N N)$	$\pi(N L)$
323 forecast= La Niña	$\pi(L E)$	$\pi(L N)$	$\pi(L L)$

324 When Bayesian updating is assumed, the uncertainty of forecasts is built into this
325 matrix. Again, assuming that the set of possible forecasts is identical to the set of
326 potential states of the world, now the diagonal elements of this likelihood matrix
327 correspond to the *hit rates* for every possible event. Given a perfect information
328 source, each of these diagonal elements will take the value of one, and all of the
329 off-diagonal elements, zero. To model imperfect forecasts, the diagonal elements are
330 assigned values of less than one, and the off-diagonal elements are permitted to be
331 greater than zero. For example, Adams et al. (1995) quantify the effect of increased
332 forecast skill by increasing the diagonal elements from 0.6 to 0.8. Note that if the
333 likelihood matrix depicts forecast uncertainty (i.e. it has *hit rates* of less than one),
334 the resultant posterior matrix will reflect this uncertainty with *post-agreement rates*
335 of less than one.

336 It is generally assumed that the posterior matrices and likelihood matrices cor-
337 rectly reflect the accuracy of forecasts. That is, the decision makers correctly assess
338 the uncertainty of the forecasts. It is also typically assumed that decision makers’
339 priors are based on climatological, or historical probabilities—in other words, that
340 their prior distributions are ‘correct.’ However, none of these assumptions have been

341 formally tested, leading some to investigate their consequences: For example, Mjelde
342 et al. (1988) present a rare illustration of the effect of the assumed prior distribution:
343 they consider four different types—climatological, prior year, ‘pessimistic’ (worst-
344 case), and ‘optimistic’ (best case)—and find that expected net returns are, indeed,
345 sensitive to the assumed prior distribution, but not necessarily in predictable ways.
346 Sonka et al. (1987) note that the use of climatological distributions as prior beliefs
347 tends to underestimate the value of forecasts (p. 1086).

348 To summarize, the imperfect nature of forecasts is represented either through pos-
349 terior matrices or likelihood matrices. Where the updating mechanism is modeled,
350 decision makers are assumed to arrive at ‘correct’ posterior distributions by perfectly
351 updating their priors. With very few exceptions, these priors are also assumed to be
352 ‘correct’—that is, the prior distributions of the farmers are identical to the absolute
353 (unconditional on forecasts) probability distributions of the outcomes. Decision mak-
354 ers are then assumed to make management decisions consistent with their posterior
355 beliefs. That is, decision makers perfectly assimilate imperfect forecasts.

356 **4 The value of imperfect forecasts: a simple ex-** 357 **ample**

358 Value estimates of forecast sources, or information systems in general, are generated
359 by comparing the value stream resulting from the decision maker’s actions in the

360 presence of forecasts (or ‘better’ forecasts), to that resulting from their absence (or
361 reference forecasts).¹⁰ Thus forecasts have value only when i) they cause decision
362 makers to choose actions that they would not not have otherwise chosen and ii) when
363 these actions lead, on average, to better outcomes.

364 Intuitively, when forecasts are less than perfect, their value is lower. Obviously,
365 when the forecast is incorrect some of the time, even the ‘right’ strategy can lead, at
366 times, to retrospectively ‘wrong’ decisions.¹¹ Less obvious is that even in the presence
367 of skilled forecasts, decision makers may not change their management strategies. If
368 the management strategies remain unchanged, forecasts, however skilled, have zero
369 value. A critical question, then, is ‘how skilled must forecasts be to induce changes in
370 management practices and thereby begin generating welfare improvements for farm-
371 ers?’

372 Empirical evidence suggests the existence of a ‘minimum-reliability threshold,’
373 below which the cognitive costs of seeking and assimilating a new (and possibly su-
374 perior) forecast source outweighs the expected benefit of doing so (See, for example,
375 Hayman et al. (2007) for a synthesis of the literature on seasonal climate forecast ac-

¹⁰Such value-of-information studies have been undertaken for various agricultural settings with different management choice sets (e.g. crop choice, planting dates, fallowing, fertilizer application) and forecast types (e.g. ENSO phase, SOI phase, rainfall terciles). For a comprehensive list, please see Meza, Hansen, and Osgood (2008).

¹¹A ‘strategy’ is defined as a complete set of decision rules for every possible forecast. For example, ‘If the forecast is El Niño, take action A; if the forecast is neutral, take action B; and if the forecast is La Niña, take action C.’

376 curacy and forecast adoption in Australia.). However, even absent such psychological
377 thresholds, existing models of imperfect forecast use suggest the existence of critical
378 threshold levels of forecast skill below which forecasts have no value whatsoever (e.g.
379 Moeller et al. (2008), Millner (2008)). That is, even if decision makers ‘pay attention’
380 to forecasts, depending on their accuracy levels, they may not induce changes in man-
381 agement practices, meaning that the forecasts still provide zero value. Millner (2008)
382 makes this point with a flexible, generalized theoretical model of Bayesian updating
383 with imperfect forecasts and explores the sensitivity of this result to various factors,
384 including the nature of the management problem and the assumed risk preferences.

385 Here, we provide a more qualitative and much simplified example: a cropping
386 model based on imperfect ENSO forecasts. Our model is loosely based on the wheat-
387 soybean-peanut-maize system in Tifton, Georgia described by Jones et al. (2000) and
388 uses their estimates of output prices and per-area input costs. However, in order to
389 maintain the focus on the mechanism of forecast assimilation, we have assumed away
390 many layers of complexity that typically make such models more realistic.

391 Every season, our farmer must choose one crop from among maize, wheat, and
392 soybean.¹² The objective of the farmer is to maximize his expected profit, and his
393 decision each year is based on the (imperfect) forecast of the ENSO phase. Suppose
394 the following: Maize yields are 10% higher in La Niña years, 10% lower in El Niño
395 years, and average (5.82 Mg/ha) in neutral years; wheat yields are 7% lower in La

¹²We exclude peanuts for the sake of simplicity.

396 Niña years, 7% higher in El Niño years, and average (4.0 Mg/ha) in neutral years;
 397 finally, soybean yields are constant (2.4 Mg/ha) across all three phases.¹³ Lastly,
 398 assume that the three phases and their forecasts occur with equal probability.

399 We depict the uncertain nature of the forecasts by assuming that the farmer, given
 400 a particular forecast (e.g. “It will be an El Niño (neutral, La Niña) year”), trusts
 401 that it will most likely be an El Niño (neutral, La Niña) year but also understands
 402 that the forecast will be wrong some of the time. That is, the *post-agreement rate*
 403 (PAR) for all three signal types can be less than unity. Using the terminology from
 404 above, we assume the farmer’s matrix of posterior probabilities to be

405

	forecast=El Niño	forecast=neutral	forecast=La Niña
outcome= El Niño	g	$(1 - g)/2$	$(1 - g)/2$
outcome= neutral	$(1 - g)/2$	g	$(1 - g)/2$
outcome= La Niña	$(1 - g)/2$	$(1 - g)/2$	g

406

407 where g is the PAR and $.3\bar{3} \leq g \leq 1$. For the sake of simplicity, we use the same
 408 PAR for all three forecast types.

409 Suppose that the farmer’s perception of the forecasts’ accuracy is identical to the
 410 actual accuracy of the forecasts and this accuracy is described by g . For every level
 411 of g , the farmer chooses an *ex ante* management strategy. An example strategy is
 412 “If the forecast is El Niño, I will plant wheat; if it is La Niña, I will plant maize,

¹³The qualitative yield responses to ENSO phases, if not the exact percentages, are based on Hansen et al. (1998). The baseline yields are made up by the authors.

413 and if it is neutral, I will plant soybean.” Given our example, this is, in fact, the
 414 optimal strategy when $g = 1$, or the forecasts are perfect. The farmer arrives at this
 415 and all other strategies by calculating, for each forecast, the expected profit from
 416 planting each crop and then choosing the crop that yields the highest expected profit
 417 conditional on the forecast.¹⁴ The expected value of the farmer’s strategy is calculated
 418 by multiplying the expected profit of each optimal action (conditional on the forecast)
 419 by the frequency of each forecast. A formal statement of the problem and specific
 420 formulae can be found in the Appendix.

421 The table below shows how the optimal strategy varies as the PAR ranges from
 422 $.3\bar{3}$ to 1. In this example, a PAR of $.3\bar{3}$ means that, given a forecast $f = k$
 423 ($k \in \{\text{El Niño, neutral, La Niña}\}$) the posterior probability of the outcome being k
 424 is identical to the prior probability of outcome k .¹⁵ This is equivalent to i) absent
 425 forecasts, the decision maker relying strictly on his prior distribution and ii) the de-
 426 cision maker hearing forecasts that are unbiased but completely uninformative (i.e.
 427 the forecasts are random draws from the historical probability distribution).

¹⁴By making the maximand—or the value to be maximized—expected profit, we inherently assume risk-neutrality on the part of the farmer. However, it is just as common for models to assume that the farmer chooses the management strategy that maximizes his/her expected utility or some other preference function. Doing so here would have unnecessarily complicated the example.

¹⁵Specifically, if the forecast is ‘El Niño,’ for example, $pr(o = E|f = E) = pr(o = E) = .3\bar{3}$.

PAR	optimal strategy			E[profit]	Value of information
(g)	El Niño	neutral	La Niña	(\$/ha)	(\$/ha)
1.0	wheat	soybean	maize	262.07	11.52
0.9	soybean	soybean	maize	258.20	7.65
.8	soybean	soybean	maize	255.26	4.71
.7	soybean	soybean	maize	252.33	1.78
.6	soybean	soybean	soybean	250.55	0
.5	soybean	soybean	soybean	250.55	0
.4	soybean	soybean	soybean	250.55	0
.33	soybean	soybean	soybean	250.55	0

428

429

430 As the PAR increases from .33 to 1 the farmer switches from a strategy of ‘soybean
431 no matter what the forecast,’ to ‘maize if La Niña, soybean otherwise,’ to ‘wheat if El
432 Niño, soybean if neutral, and maize if La Niña.’¹⁶ Notice that the optimal strategy of
433 the farmer does not change from his default strategy (i.e. his strategy when $g = .33$)
434 until the PAR exceeds 0.6. Because the information does not induce any change in
435 behavior up to this point, the forecasts—despite being skilled—generate zero marginal
436 value. Once this minimum reliability threshold is surpassed, however, the forecasts
437 begin to modify the farmer’s behavior, generating value.¹⁷

¹⁶While it is highly unrealistic that a farmer would switch crops on a whole-farm basis, this is a result of our simplifying model assumptions.

¹⁷The same qualitative result would have been obtained under risk aversion.

438 This simple example illustrates that even if skilled forecasts are available, and
439 even if farmers are attuned to these forecasts, forecasts may have no value if they
440 are not ‘accurate enough.’ It is consistent with the numerous studies reporting large
441 percentages of farmers being aware of forecasts but far smaller percentages ‘using
442 the forecasts,’ or incorporating the forecasts into their management practices in dis-
443 cernible ways.

444 **Conclusion and recommendations**

445 The past few decades saw tremendous advances in weather and climate forecasting
446 ability. These improvements opened up the possibility of strategic adaptation of agri-
447 cultural management in anticipation of weather and climate outcomes, resulting in a
448 profusion of studies estimating the value of weather and climate forecasts. Estimated
449 values from this literature were, in many cases, substantive, implying that farmers
450 could significantly benefit from forecasts. Yet the response from farmers, to date,
451 does not appear commensurate with the values suggested by the studies.

452 A farmer’s decision to rely on a forecast source is likely a function of many things-
453 —here, we make the case that forecast quality may still pose a significant obstacle.
454 Despite recent gains in forecasting ability, forecasts—especially those for the longer
455 term—are far from certain. It is possible that forecasts are still not ‘certain enough’
456 for the purposes of strategic agricultural management, but the vast majority of our
457 current models of forecast use do not allow for such a possibility. Even the second-

458 generation, imperfect-forecast models are oftentimes calibrated to consider farmer
459 behavior in response to forecasts over unrealistically high ranges of accuracy. More-
460 over, our applied theoretical models appear, for the most part, to be happily self
461 replicating, completely independent of the growing, (albeit qualitative) empirical lit-
462 erature on forecast quality, farmer perceptions of forecast quality, and farmer use of
463 imperfect forecasts.

464 Estimates of climate and weather forecasts value will continue to generate unreal-
465 istic results unless forecast assimilation models better reflect actual forecast quality
466 levels and farmer behavior. Obtaining meaningful models of forecast use requires
467 the convergence of our models with real farmer behavior. The obvious, but difficult,
468 solution is to nudge our models closer to observed farmer behavior. To this end, we
469 have two recommendations:

470

471 *Make forecast uncertainty a standard feature in models of forecast use and value.*

472 Models should reflect the imperfect nature of forecasts. Not only should studies as-
473 sume less-than-perfect forecasts, but they should simulate decision-making behavior
474 in response to a wider (and lower) range of accuracy levels. They should make ex-
475 plicit their hypothesized models of forecast assimilation—that is, how farmers weigh
476 forecasts against their subjective priors (if at all), the bases of these priors, and the
477 translation of this information into management decisions. Most importantly, these
478 model assumptions should be explicitly tested and continually updated based on em-

479 pirical findings.

480

481 *Empirically test assumptions of forecast assimilation and let the findings inform fu-*
482 *ture models.*

483 Some empirical studies of farmer forecast use exist—see, for example, Artikov et al.
484 (2006), Hu et al. (2006) and Marx et al. (2007)—however, these studies do not nec-
485 essarily test for specific assumptions made in models of imperfect forecast use. For
486 example, below a certain perceived level of accuracy, farmers may ignore forecasts
487 altogether; at higher levels, they may update their priors; and at still higher levels
488 of accuracy, they may treat forecasts as perfect. However, without any sort of input
489 from those on the ground, observing (i.e. sociologists, extension agents, and farmers
490 themselves), this all remains speculation.

491 It is not at all surprising that models of forecast use have never been tested
492 empirically when one considers the ‘ideal’ dataset: panel data on forecasts, forecast
493 accuracy measures, and farmer responses. Such data are difficult, if not impossible, to
494 find observationally. Nonetheless, this empirical void could be filled with data from
495 framed field experiments (for example, something akin to Menapace, Colson, and
496 Raffaelli (2012)) or, at the least, qualitative interviews and focus groups designed
497 specifically to vet models of forecast use.

498 This latter recommendation is a restatement of the perennial ‘ivory tower’ problem—
499 or rather, the ‘ivory *towers*’ problem—in that adequate communication is not taking

500 place between the disciplines (the towers), much less between the modelers and those
501 they claim to model. Howden et al. (2007) note that challenges that are multi-
502 disciplinary in nature require multi-disciplinary solutions. Pielke Jr. and Carbone
503 (2002) claim that the U.S. has not yet fully benefited from public investment in
504 the ‘weather prediction enterprise.’ They note, “For the process to work effectively,
505 success is necessary in all three elements of the forecast process: prediction, commu-
506 nication, and use (p. 400).” While the authors’ statement here refers to the actual
507 use of forecasts, the same is true of our *models* of use; absent increased efforts to
508 integrate farmer input and empirical observations of forecast use into our models,
509 we can never hope to estimate the true value of the burgeoning ‘weather prediction
510 enterprise.’

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649 **Appendix: Formal statement of the example**

650 *The decision maker's problem and choice set*

651 Each year, the farm manager is faced with the problem of what to plant on his farm:
 652 maize (m), soybean (s), or wheat (w). His objective is to maximize his expected
 653 per-area profit.

654 His whole-farm profit in any season is a function of his crop choice ($a \in \mathbf{A} =$
 655 $\{m, s, w\}$), the ENSO phase outcome ($o \in \{E, N, L\}$), the output prices of the crops
 656 (p_m, p_s, p_w) , and the per-area input costs for the crops (c_m, c_s, c_w) . We assume con-
 657 stant crop prices and production costs. The prices (in USD/Mg) are 101 for maize,
 658 222 soybeans, and 120 for wheat. The costs (in USD/ha) are 364 for maize, 282 for
 659 soybeans, and 260 for wheat. Prices and input costs are derived from Jones et al.
 660 (2000). The yield (y) for each crop is a function of the ENSO phase; we assume the
 661 following yields (in Mg/ha):

$$y_m(E) = 5.24 \quad y_m(N) = 5.82 \quad y_m(L) = 6.40$$

$$y_s(E) = 2.40 \quad y_s(N) = 2.40 \quad y_s(L) = 2.40$$

$$y_w(E) = 4.28 \quad y_w(N) = 4.00 \quad y_w(L) = 3.72$$

662 Per-acre profit depends on the crop choice and the ENSO phase outcome:

$$\text{profit} = j(a, o) = \begin{cases} p_m y_m(o) - c_m & \text{if } a = m \\ p_s y_s(o) - c_s & \text{if } a = s \\ p_w y_w(o) - c_w & \text{if } a = w \end{cases}$$

663 Prior to planting, the farmer receives a forecast f ($f \in \{E, N, L\}$). He understands
664 that any particular signal will be correct $g\%$ of the time, and when it is incorrect,
665 the odds are evenly split between the two non-forecasted outcomes. (Please see the
666 posterior matrix in the main text.) For each of the three potential forecasts, the
667 farmer must decide what his best response will be. To do this, he vets all three
668 crops and chooses the one that results in the highest expected profit, conditional on
669 the forecast. For example, for the forecast ‘El Niño,’ the expected profit of any one
670 alternative a is

$$\begin{aligned} E[\text{profit}|f = E, a] &= \sum_{k=\{E,N,L\}} pr(o = k|f = E)j(a, k) \\ &= g \cdot j(a, E) + (1 - g/2) \cdot j(a, N) + (1 - g/2) \cdot j(a, L). \end{aligned} \quad (1)$$

671 The best response a_E^* to the El Niño forecast is

$$a_E^* = \max_{a \in \mathbf{A}} E[\text{profit}|f = E, a].$$

672 By repeating this process for the two remaining forecasts, he farmer identifies his
673 optimal strategy $\{a_E^*, a_N^*, a_L^*\}$ from the choice set $\mathbf{A} \times \mathbf{A} \times \mathbf{A}$.

674

675 *The expected value of the optimal strategy*

676 The expected value of the optimal strategy is the sum of the expected profits from
677 using the best response to each forecast, weighted by the frequency of each forecast.

$$E[\text{profit}]^* = \sum_{k=\{E,N,L\}} pr(f = k)E[\text{profit}|f = k, a_k^*] \quad (2)$$

678 Although it is not readily apparent in equation 2 above, the optimal strategy—and
 679 therefore expected profit—is very much a function of the accuracy measure g , as
 680 equation 1 shows.

681

682 *The value of forecasts and increases in forecast quality*

683 The monetary value of information is defined as the difference in expected value of
 684 decisions made in the presence of the information and the expected value of decisions
 685 made in its absence. Similarly, the value of increasing the accuracy of the information
 686 is the difference in expected value between decisions made using the improved infor-
 687 mation and those made using information of some reference accuracy level. In this
 688 example, we use as our reference the expected value of the optimal strategy based
 689 on a scenario in which there are no forecasts or, equivalently, one in which there are
 690 forecasts, but they are completely uninformative ($PAR = .3\bar{3}$). In such a situation,
 691 we assume that the farmer would have chosen a single crop $\hat{a}$ that solves the following
 692 problem:

$$\max_{\hat{a} \in \mathbf{A}} E[\text{profit}|\hat{a}]$$

$$\text{where } E[\text{profit}|\hat{a}] = pr(o = E)j(\hat{a}, E) + pr(o = N)j(\hat{a}, N) + pr(o = L)j(\hat{a}, L)$$

693 Here the farmer identifies the cropping pattern that yields the highest expected profit,
 694 on average. It is a static strategy in that the farmer will do the same thing each season.
 695 Our baseline value is the maximand to the above problem:

$$E[\text{profit}]^* = pr(o = E)j(\hat{a}^*, E) + pr(o = N)j(\hat{a}^*, N) + pr(o = L)j(\hat{a}^*, L) \quad (3)$$

696 The value of information—or having the forecasts—is the difference in expected profit
697 between the optimal dynamic strategy (equation 2) and the optimal static strategy
698 (equation 3).