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Research-Policy Linkages

Empirical Evidence from Agroeconomic Research in India

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Policy-making processes in developing countries often continue to operate devoid of evidence. In this study, we explore the research-policy linkages between the agroeconomic research system (AERS) and the agricultural policy system (APS) in India. Specifically, we examine questions directed to the Ministry of Agriculture and Farmers' Welfare in the two houses of the national parliament—the House of the People (Lok Sabha) and the Council of States (Rajya Sabha)—and filter them for key issues that confront the APS. In addition, using the list of research articles published in two major national agricultural economics journals, we examine the alignment of the AERS toward addressing pressing policy issues. We use 6,465 questions raised by elected representatives in the parliamentary houses and 377 research articles, both during the period 2014–2018. We use machine learning techniques for information retrieval because the required information is hidden as non-numerical text. Using tag clouds (lists of words by frequency), we identify key divergences between the concerns of the APS and the research focus of the AERS, and explore their linkages. To broaden our understanding, we employ latent Dirichlet allocation, a natural language processing technique that identifies crucial issues and automates their classification under appropriate clusters, to examine synergies between the research and policy systems. Results show remarkable alignment between the AERS and the APS, invalidating the two-communities hypothesis. We identify persistent issues in the policy domain that require the support of the research system, as well as potential areas for research system realignment.

Keywords: research-policy linkages, agricultural economics, machine learning, latent Dirichlet allocation, India.

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ACRONYMS

AERS	agroeconomic research system
APS	agricultural policy system
DAC&FW	Department of Agriculture, Cooperation and Farmers' Welfare
DARE	Department of Agricultural Research and Education
ICAR	Indian Council of Agricultural Research
LDA	latent Dirichlet allocation
LSA	latent semantic analysis
MoAFW	Ministry of Agriculture and Farmers' Welfare
MoFAH&D	Ministry of Fisheries, Animal Husbandry and Dairying
MSP	minimum support price
NARS	national agricultural research system
pLSA	probabilistic latent semantic analysis
SDGs	Sustainable Development Goals

1. Introduction

Achieving the United Nations Sustainable Development Goals (SDGs) in developing countries crucially depends on the nature and speed of their economic growth and transformation. Their transformation process, in turn, depends on appropriate policies and strategies backed by adequate investments, institutional support, and efficient governance in implementation. Policy development processes, however, continue to be haphazard and sometimes remain devoid of scientific evidence. This is largely due to the disengagement of the policy and research systems at the national level. The academic community, on the one hand, continues to pursue its research interests, while the need for evidence in policy making may substantially differ from those interests. On the other hand, there is also a tendency to ignore research evidence in the policy process because such evidence is sometimes believed to be irrelevant to ground-level problems. This divergence between the research and policy systems often results in inappropriate policies and, at the minimum, can delay achievement of the SDGs.

Literature on research-policy linkages in developing countries remains scanty. Research generates objective evidence for informed policymaking. Early involvement of policy makers in the research process may guarantee successful research utilization (La Brooy and Kelaher 2017). Yet the research by itself is not going to guarantee this (Black 2001). The renowned two-communities theory observes that the academicians who generate research outputs, and the policy practitioners who utilize these outputs to bring desired social outcomes, are perceived to live in isolated communities operating under unlinked rules, languages, and reward systems (Caplan 1979; Dunn 1980). Anheier (2019) presented a clear divide between these communities, noting that academia is driven mainly by analytics, bureaucrats function as process optimizers, and policy makers serve as the seekers of actionable answers. In a nutshell, policy makers have yet to utilize academic research effectively (Nutley, Walter, and Davies 2007).

Successive research has refuted the two-communities conceptualization to varying degrees, but it has not left a level playing field. Although Newman, Cherney, and Head (2015) observed notable interactions among the research and policy communities, they also made note of the inherent divide within the latter, arguably between politicians and bureaucrats. Desmarais and Hird (2014) showed extensive use of scientific research in policy making but also narrated excessive dependence on article citations and the scholarliness of research journals. On a similar line, Perche (2011) brought into context the influential role path dependency plays during contemporary policy making, leading to the road of rewriting the past. The role of cross-sectoral knowledge in the policy design process is also rather limited. Only recently has practice transitioned from designing policy based on within-sector mandates to incorporating cross-sectoral thinking (Venghaus and Hake 2018). Deriving alternative readings in evidence-based policy making is perceived to create uncomfortable knowledge, thus generating flawed policy prescriptions (Saltelli and Giampietro 2017). This knowledge base is believed to turn even more fragile when nonscientific representations are abandoned (Bremer 2017).

In real-world situations, the policy impact any research could generate depends not just on the knowledge it delivers but also on post-research dissemination actions and other contextual factors (Newson et al. 2015). As if to bolster this assertion, Banks (2015) noticed that policy practitioners with a research background are generally more inclined toward using research. The author also highlighted other factors responsible for restricting research utilization by the policy system: the limited focus of research on practical policy matters, attitudinal barriers, time constraints, and lack of supportive behavior from political leaders. These factors lead scientists sometimes to play influential roles in the policy process but at other times just to cherry-pick the contexts (Jørgensen 2011). Oversupply of facts is the other factor observed sometimes to hamper the use of science for governance and policy design (Kovacic 2017; Kovacic and Giampietro 2015). Within the scientific frame, notably on methodological choices, quantitative drives have been found to illuminate socially legitimate objects and obfuscate objects that can't be legitimated (Sareen, Saltelli, and Rommetveit 2020). Together with the call to revisit the ethics of using algorithms in public policy making,

it is common to notice rising concerns about inferring from statistics and mathematical modeling (Saltelli 2020).

Despite such concerns, the role currently played by mathematics and statistics in policy making seems irreversible. The gradual rise in the use of algorithms for public policy making has added substance to this proposition. The applications of artificial intelligence and machine learning algorithms have expanded beyond mining the genome (Mohimani et al. 2014; Cao et al. 2019), discovering antibiotics (Stokes et al. 2020), automating biomedical relation extraction (Hong et al. 2020), and replacing fossil fuels (Zhong et al. 2020). They now stretch to organizational decision making (Bader and Kaiser 2019) and designing public policy frameworks as well. Some of the direct applications in public policy making include but are not limited to developing health care programs (Obermeyer and Mullainathan 2019) and health policies (Ashrafian and Darzi 2018), handling refugee assignments (Bansak et al. 2018), rendering judgments in law (Kleinberg et al. 2018), and making hygiene inspections in the food sector (Glaeser et al. 2016). Although public perceptions decline (Smith 2018) even as public trust in algorithms gains in importance (Zerilli et al. 2019), transparency measures such as interactive and "white-box" processes are found to bring confidence in such intelligence systems (Cheng et al. 2019). Machine learning methods are found to excel in predictive accuracy over statistical modeling (Bzdok, Altman, and Krzywinski 2018). Developments in quantum algorithms (Biamonte et al. 2017) promise to further broaden the applications of machine learning in the years to come.

Discussions on conceptual and empirical evidence reiterate the need for striking a balance between scientific and nonscientific values in public policy design as well as when choosing among the plethora of evidence the science generates from multiple methodologies. The present study is an attempt in this direction. We build our current study on two key pillars. First, to our knowledge, most of the literature debating the two-community hypothesis examines research-policy relations in developed countries. So the methods they adopt and outcomes they derive won't be applicable for countries other than the developed nations, given the difference in the institutional arrangements and governance policies. Primarily, there hasn't been any study on the Indian agriculture sector to inquire into the knowledge-brokering process between research and policy institutions, despite the sector's experiencing an array of reforms in the recent past to improve farmers' welfare. Second, again in the Indian context, the real-time applications of machine learning algorithms to explore the nexus are almost nil.[1] Methodology in the past has generally involved only direct interviews and opinions.

In the present study, we attempt to explore the bidirectional knowledge interaction between the research and policy systems in the Indian agroeconomic research system (AERS) and the country's agricultural policy system (APS). We inquire about how far the agricultural policies and reform processes designed and executed by the political system and bureaucracies are evidence-based, and reciprocally, the degree of alignment of the research proceedings with the policy demands. As a novel approach, we use questions directed to the Ministry of Agriculture and Farmers' Welfare (MoAFW) by elected representatives in the Indian parliamentary houses during 2014–2018 to extract key issues the APS confronts, and research articles published during the same period in two major national journals for agricultural economics to trace the AERS's alignment toward meeting the APS's key issues. About 6,465 questions were directed to the MoAFW in the two houses of parliament over the study period, and 377 research articles were published.[2]

In the next section, we briefly discuss the organizational setup of the national agricultural research system (NARS), AERS, and APS in India. In the following section, we describe the nature of the data utilized, the

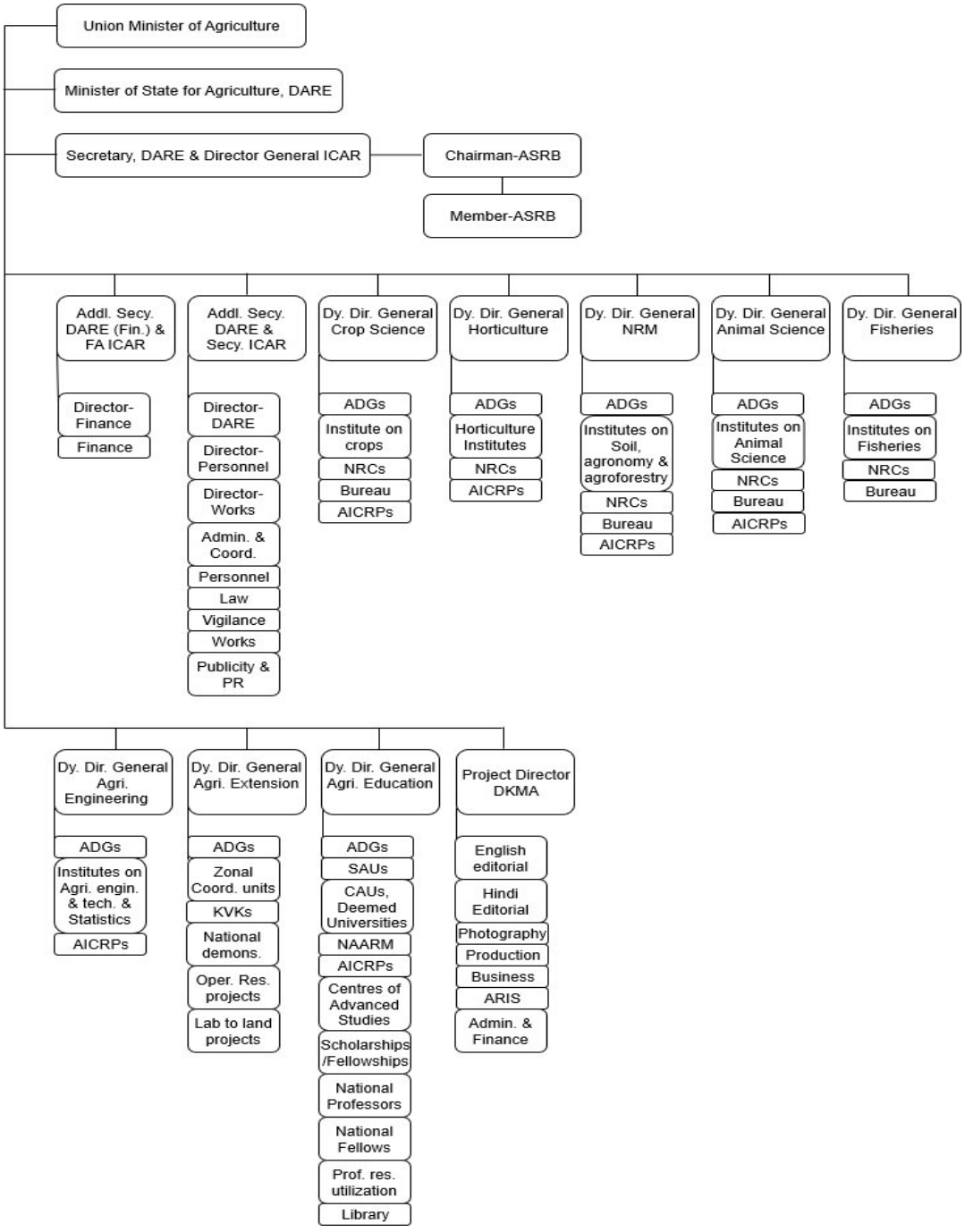
[1] Kattumuri (2015) explored relations between evidence and policy in the Indian context but not within a machine learning framework.
[2] Further details are in the section titled "Data and Design of Inquiry."

design of the inquiry, and the analytical framework adopted. We then proceed to discuss the results and critical observations in the following section and, finally, provide concluding remarks.

2. The Agricultural Research and Policy Systems in India

The NARS in India comprises the Indian Council of Agricultural Research (ICAR) as well as the central research institutes and national research centers established by ICAR. ICAR is an autonomous organization operating under the Department of Agricultural Research and Education (DARE) of the MoAFW. It is the apex body that coordinates, guides, and manages research (and education) in agriculture and allied sciences such as horticulture, fisheries, and animal sciences. Including 64 central research institutes and 15 national research centers, about 102 institutes carry out primary, applied, and social science research under ICAR's guidance. The union (national) agricultural minister acts as the ex officio president. An officer who serves as both secretary of DARE and director general of ICAR also serves as the principal executive officer of the council, assisted by two additional secretaries, eight deputy directors general, and eight additional directors general. The organizational structure of ICAR is displayed in Figure 1.

Figure 1. Organogram: Indian Council of Agricultural Research



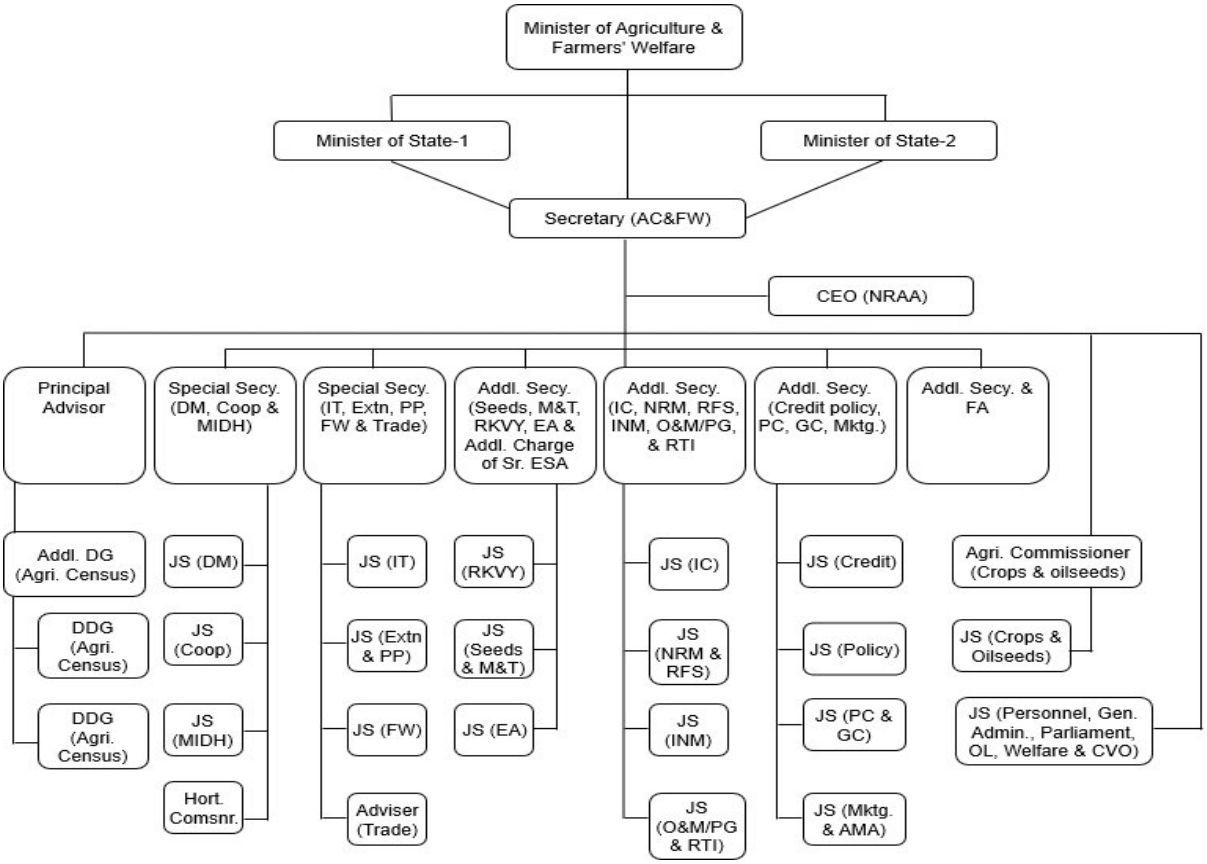
Source: Indian Council of Agricultural Research.
Note: ADG = assistant director general; AICRP = all India coordinated research project; ARIS = agriculture research information system; ASRB = agricultural scientists recruitment board; CAU = central agricultural university; DARE = department of agricultural research and education; DKMA = directorate of knowledge management; FA = financial advisor; ICAR = Indian Council of Agricultural Research; KVK = krishi vigyan kendra; NAARM = national academy of agricultural research management; NRM = natural resource management; PR = public relations; SAU = state agricultural university.

The AERS[3] comprises research institutions and departments that focus on agricultural economics research. Of more than 5,000 researchers in ICAR (ICAR 2020), about 13 percent are involved in research related to socioeconomic policies (Stads et al. 2016). Besides these, more than 17,000 researchers are spread across the state agricultural universities and 4.3 percent fall in AERS, with their thrust in education (teaching). Thus, on average, about 1,400 researchers concentrate on critical issues in agricultural economics.

The MoAFW is a nodal agency that designs and implements agricultural policies at the center. It consists of two departments, (1) the Department of Agriculture, Cooperation and Farmers' Welfare (DAC&FW), and (2) DARE. The Department of Animal Husbandry, Dairying and Fisheries, which was the third constituent under the MoAFW earlier, now operates as two independent departments, (1) the Department of Animal Husbandry and Dairying, and (2) the Department of Fisheries, both under the newly created Ministry of Fisheries, Animal Husbandry and Dairying, or MoFAH&D (Department of Animal Husbandry and Dairying 2020; Department of Fisheries 2020). The DAC&FW is headed by the union minister, assisted by two state ministers. The administrative body is headed by a secretary, who is aided by a principal advisor as well as additional and joint secretaries. The organograms of different departments under MoAFW and MoFAH&D are presented in Figures 2–5.

[3] By AERS, we refer to institutes and departments explicitly dealing with agricultural economics within NARS.

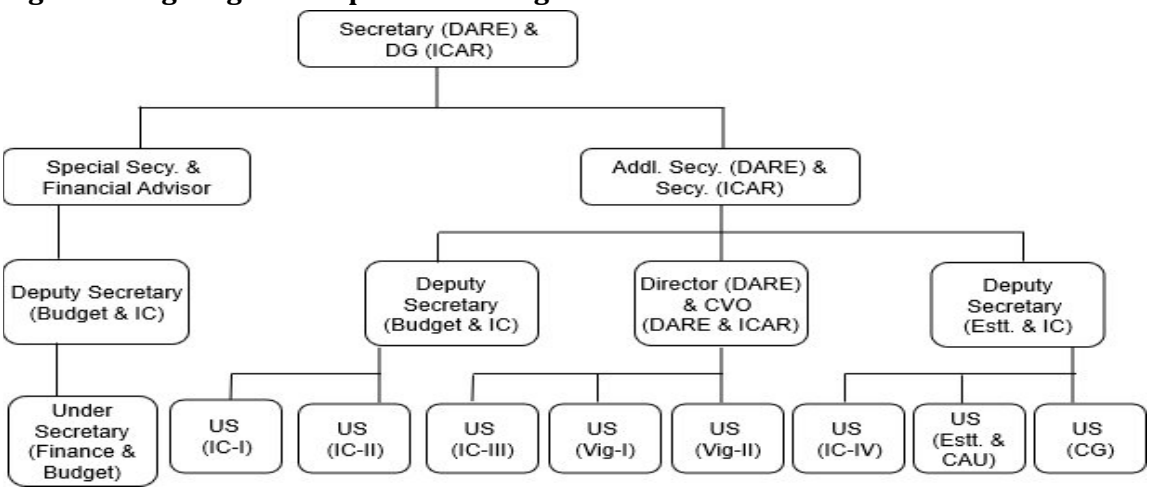
Figure 2. Organogram: Department of Agriculture, Cooperation and Farmers' Welfare



Source: Department of Agriculture, Cooperation and Farmers' Welfare.

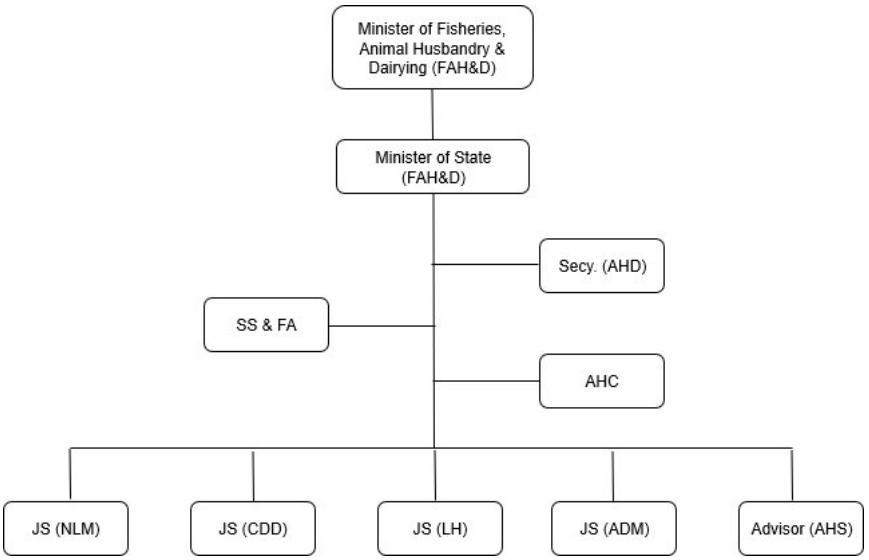
Note: AC&FW = agriculture, cooperation and farmers' welfare; AMA = agricultural marketing advisor; CEO = chief executing officer; CVO = chief vigilance officer; DDG = deputy director general; DG = director general; DM = drought management; EA = economic administration; ESA = economic and statistical advisor; FA = financial advisor; FW = farmers welfare; GC = general coordination; IC = international cooperation; INM = integrated nutrient management; IT = information technology; JS = joint secretary; M&T = mechanization and technology; MIDH = mission for integrated development of horticulture; NRAA = national rainfed area authority; NRM = natural resource management; O&M/PG = organization & methods/public grievances; OL = official language; PC = plan coordination; PP = plant protection; RFS = rainfed farming system; RKVY = rashtriya krishi vikas yojana; RTI = right to information.

Figure 3. Organogram: Department of Agricultural Research and Education



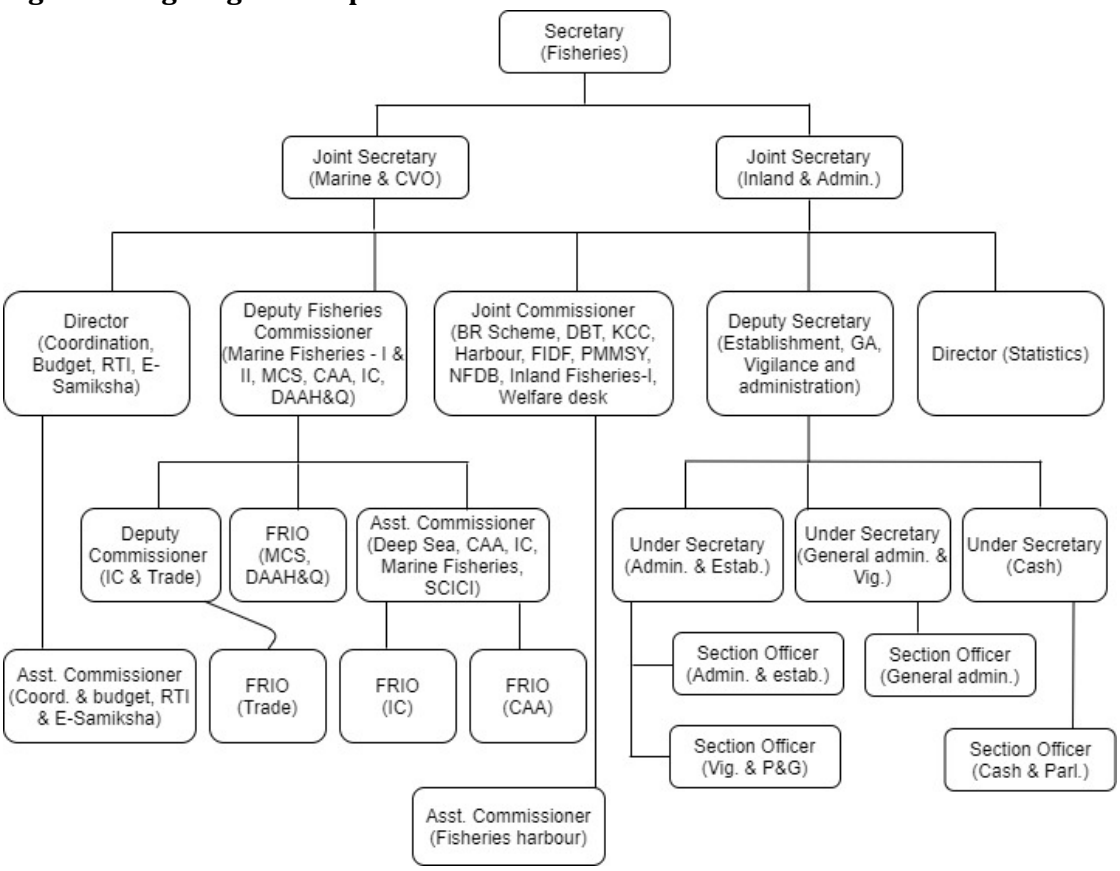
Source: Department of Agricultural Research and Education.
Note: CAU = central agricultural university; CG = consultative group (CG centres); CVO = chief vigilance officer; DARE = department of agricultural research and education; Estt. = establishment; IC = international cooperation; ICAR = Indian council of agricultural research; US = under secretary; Vig = vigilance.

Figure 4. Organogram: Department of Animal Husbandry and Dairying



Source: Department of Animal Husbandry and Dairying.
Note: ADM = administration; AHC = animal husbandry commissioner; AHD = animal husbandry and dairying; AHS = animal husbandry statistics; CDD = cattle and dairy development; FA = financial advisor; FAH&D = fisheries, animal husbandry and dairying; JS = joint secretary; LH = livestock health; NLM = national livestock mission; SS = special secretary.

Figure 5. Organogram: Department of Fisheries



Source: Department of Fisheries.

Note: BR = blue revolution; CAA = coastal aquaculture authority; CVO = chief vigilance officer; DAAH&Q = directorate of aquatic animal health and quarantine; DBT = direct benefit transfer; FIDF = fisheries and aquaculture infrastructure development fund; FRIO = fisheries research investigation officer; GA = general administration; IC = international cooperation; KCC = kissan credit card; MCS = monitoring, control and surveillance; NFDB = national fisheries development board; P&G = public grievances; PMMSY = pradhan mantri matsya sampada yojana; RTI = right to information; SCICI = shipping credit and investment company of India limited; Vig. = vigilance.

3. Data and Design of Inquiry

We retrieved information from two sets of text corpora.[4] The first set of corpora archives the questions raised by elected representatives to the MoAFW in both houses of parliament, along with their answers. The parliament of India comprises two houses, the House of the People (Lok Sabha) and the Council of States (Rajya Sabha). Representatives elected directly by the citizens across 28 states and 8 union territories constitute the House of the People. The house allows a maximum of 552 representatives, of whom 530 are selected through states and the other 20 through union territories. The president of India nominates the remaining 2 from the Anglo-Indian community. Representatives of the Council of States are elected indirectly by the states' legislative assembly members and the union territories' electoral college members.

[4] A *text corpus* is a large collection or set of structured texts; *corpora* is the plural form of *corpus*.

At the House of the People, representatives raise questions on the government's national and international policies the during the first hour of sitting,[5] and the respective ministers answer them. The case is similar at the Council of States. Answers are demanded either in verbal form (known as the "starred category" of questions) or in written form (the "unstarred category"). We take the list of starred and unstarred questions directed to the MoAFW as a proxy database from which to filter key issues the APS confronts, with the frequency of specific topics being raised determining the actions of the bureaucracy and political system. In total, 6,465 questions were identified between 2014 and 2018, with a breakdown of 3,647 from the House of the People and 2,818 from the Council of States[6] (Parliament of India, Council of States 2019; Parliament of India, House of the People 2019) (Table 1).

Table 1. Volume of text corpora

Research domain (2014–2018)	
Journal	**Studies covered**
a. *Agricultural Economics Research Review*	242
b. *Indian Journal of Agricultural Economics*	135
Total	377
Policy domain (2014–2018)	
Parliamentary house	**Questions covered**
House of the People (Lok Sabha)	
a. Starred	322
b. Unstarred	3,325
Total (a)	3,647
Council of States (Rajya Sabha)	
a. Starred	268
b. Unstarred	2,550
Total (b)	2,818
Total (a + b)	6,465

Source: Authors.

Our second set of text corpora reflects research activities in the AERS. The NARS comprises basic, applied, and social science components, and shares its research outcomes in journal articles, project reports, books, annual reports, research bulletins, policy briefs, and the like. The present study considers the AERS of the NARS alone.[7] Because new knowledge and technologies developed in basic and applied sciences ultimately converge toward addressing the social and economic welfare of farm communities, the AERS is taken to reflect outcomes of both primary and applied sciences in the form of assessing the economic viability of new technologies and their technical feasibility. Further, the AERS directly addresses (1) the impact of these technologies and the implications of key issues ranging from profits to prices, risks to remuneration, and resource scarcity to sustainability, and (2) strategies to overcome difficulties as well as pathways for income enhancement. To capture the entire spectrum of research activities carried out in the AERS, we analyze the research articles published in two major journals of agricultural economics, *Agricultural Economics Research Review* and *Indian Journal of Agricultural Economics*.[8] Although multiple journals

[5] Known as "Question Hour."
[6] The corpora also contain answers to the questions raised, but we use only the questions.
[7] There are other national and international institutes involved in agricultural economics research. We consider only the institutes under NARS in the present study.
[8] Though other forms of publications, discussed earlier, could also be considered, we chose only published journal articles to avoid duplication of issues. Relying on just two major national journals and excluding certain documents and publications from other national and international institutions is a limitation of the present study.

around the world deal with agricultural economics, these two journals were selected given their national thrust. About 377 research articles published between 2014 and 2018 are considered for the study.

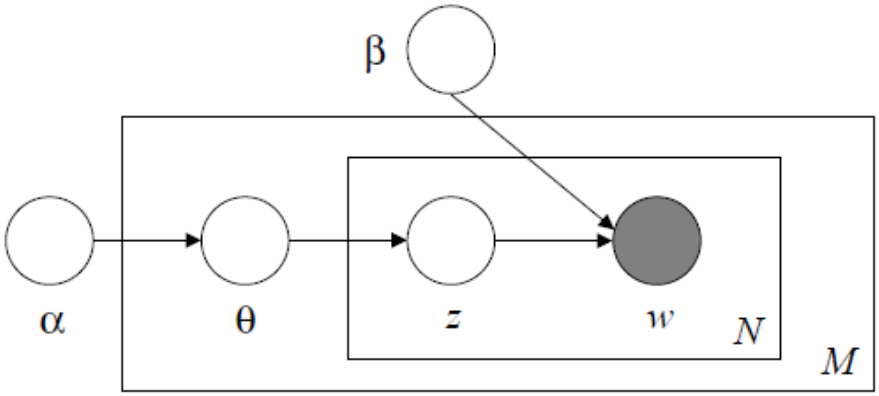
4. Analytical Framework

The information in our text corpora is in a non-numerical format, so the analytical strategy to study the nexus between AERS and APS would be to adopt a suitable information retrieval algorithm or technique that could extract information of choice in the desired format. For instance, assume that we could identify the most pressing issues in a specific time period that the APS seeks to solve and classify them under a set of topics. Assume also that a similar topic-based classification of issues can be carried out for the AERS as well. Establishing linkages between these two sets of topic classifications allows one to understand how far the research and policy systems are synchronized to address agrarian concerns. If and when there exists a synergy, we could believe that there are information exchange and feedback processes between the systems. The parliamentary questions and research articles are used to test for this synergy. Note that for the parliamentary data, only the questions are used during information processing, not the answers, which would introduce subjectivity issues. Similarly, only the titles of the research articles are used, on the assumption that adding the entire content might exert the influence of each article's literature section, thus biasing results—that is, the volume of literature surveyed in the articles, and repeated citations of certain studies, would inflate the number of appearances of particular issues in the results.

In the domain of machine learning, multiple techniques come forward to execute this strategy. Term frequency–inverse document frequency, for instance, combines the concept of weighing the frequency of words of interest (Luhn 1957) with that of imposing inverse weights on the most frequent word in the document set (Jones 1972), thus allowing one to extract the important issues. But employing this method is noted to offer smaller dimension reduction and to reveal small statistical structures contained within and between the documents (parliamentary questions and article topics, in the present context). Latent semantic analysis (LSA), introduced by Dumais and colleagues (1988) and Deerwester and others (1990), is observed to perform better in dimension reduction. It uses linear algebra together with singular value decomposition during the information retrieval process. Probabilistic latent semantic analysis (pLSA), which uses mixture decomposition derived from a latent class model (Hofmann 1999), was developed as an alternative to LSA.

Blei, Ng, and Jordan (2003) observed the pLSA approach to be "incomplete" because it doesn't provide a probabilistic model at the document level, and because it leads to overfitting and probability assignment problems. To counter these problems, they introduced latent Dirichlet allocation (LDA), a generative probabilistic model that applies the theorem of de Finetti (1990) combined with the exchangeability assumption (Aldous 1983). LDA is a hierarchical model (Figure 6) that assumes the words contained in each document emerge from a mixture of topics that are latent or unobservable. Each topic is modeled over underlying topic probabilities. A refined version of this approach even models successful correlations among the topics (Blei and Lafferty 2007). For the present purpose, we employed the LDA technique to extract key issues in the APS and AERS, and classify them under different topics.

Figure 6. Graphical representation of latent Dirichlet allocation technique



Source: Blei, Ng, and Jordan (2003).
Note: α = topic distribution per document; β = word distribution per topic; θ = topic distribution for document *M*; *w* = the specific word; *z* = the topic of the *N*th word in document *M*.

As Blei, Ng, and Jordan (2003) explained, given text corpus *D*, for *w* documents, the generative processes assumed in the LDA technique are as follows:

1. Choose $N \sim \text{Poisson}(\xi)$
2. Choose $\theta \sim \text{Dir}(\alpha)$
3. For each of the *N* words w_n,
   a. Choose a topic $z_n \sim \text{Multinomial}(\theta)$
   b. Choose a word w_n from $p(w_n|z_n,\beta)$, a multinomial probability conditioned on topic z_n.

For the topic mixture θ, set of *N* topics *z*, set of *N* words *w*, and parameters α and β, the joint distribution is given by

$$p(\theta, \boldsymbol{z}, \boldsymbol{w}|\alpha,\beta) = p(\theta|\alpha)\prod_{n=1}^{N} p(z_n|\theta)p(w_n|z_n,\beta). \quad (1)$$

The document's marginal distribution is given by

$$p(\boldsymbol{w}|\alpha,\beta) = \int p(\theta|\alpha)\Big(\prod_{n=1}^{N} \sum_{z_n} p(z_n|\theta)p(w_n|z_n,\beta)\Big)d\theta, \quad (2)$$

and the corpus' probability is given by

$$p(D|\alpha,\beta) = \prod_{d=1}^{M} \int p(\theta_d|\alpha)\Big(\prod_{n=1}^{N_d} \sum_{z_{dn}} p(z_{dn}|\theta_d)p(w_{dn}|z_{dn},\beta)\Big)d\theta_d. \quad (3)$$

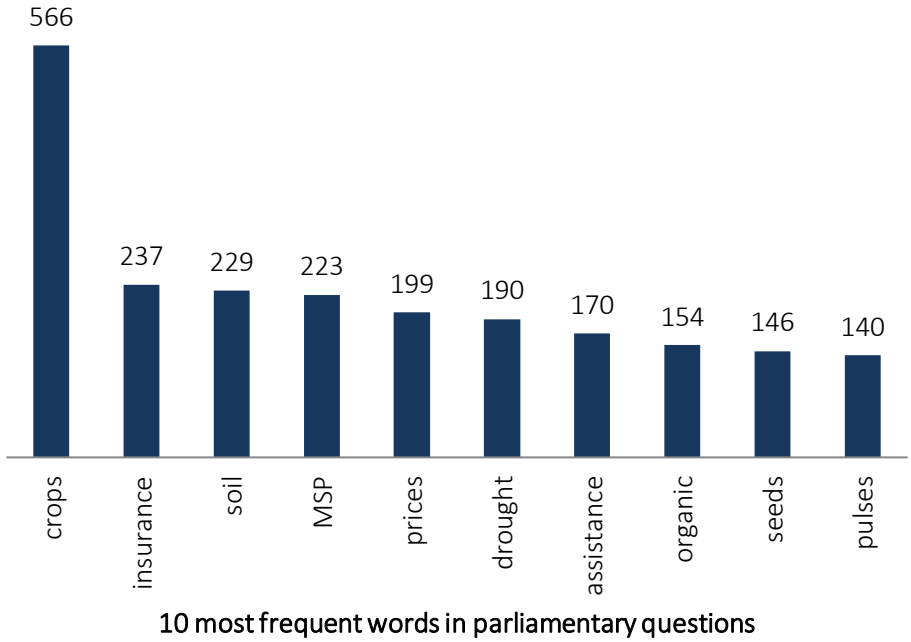
In equations 1–3, as in Figure 6, α refers to topic distribution per document, β refers to word distribution per topic, θ refers to topic distribution for document *m*, φ refers to word distribution for topic *k*, *z* is the topic for the *n*th word in document *M*, and *w* is the specific word.

5. Results and Discussion

Key Issues in the Agricultural Policy Domain

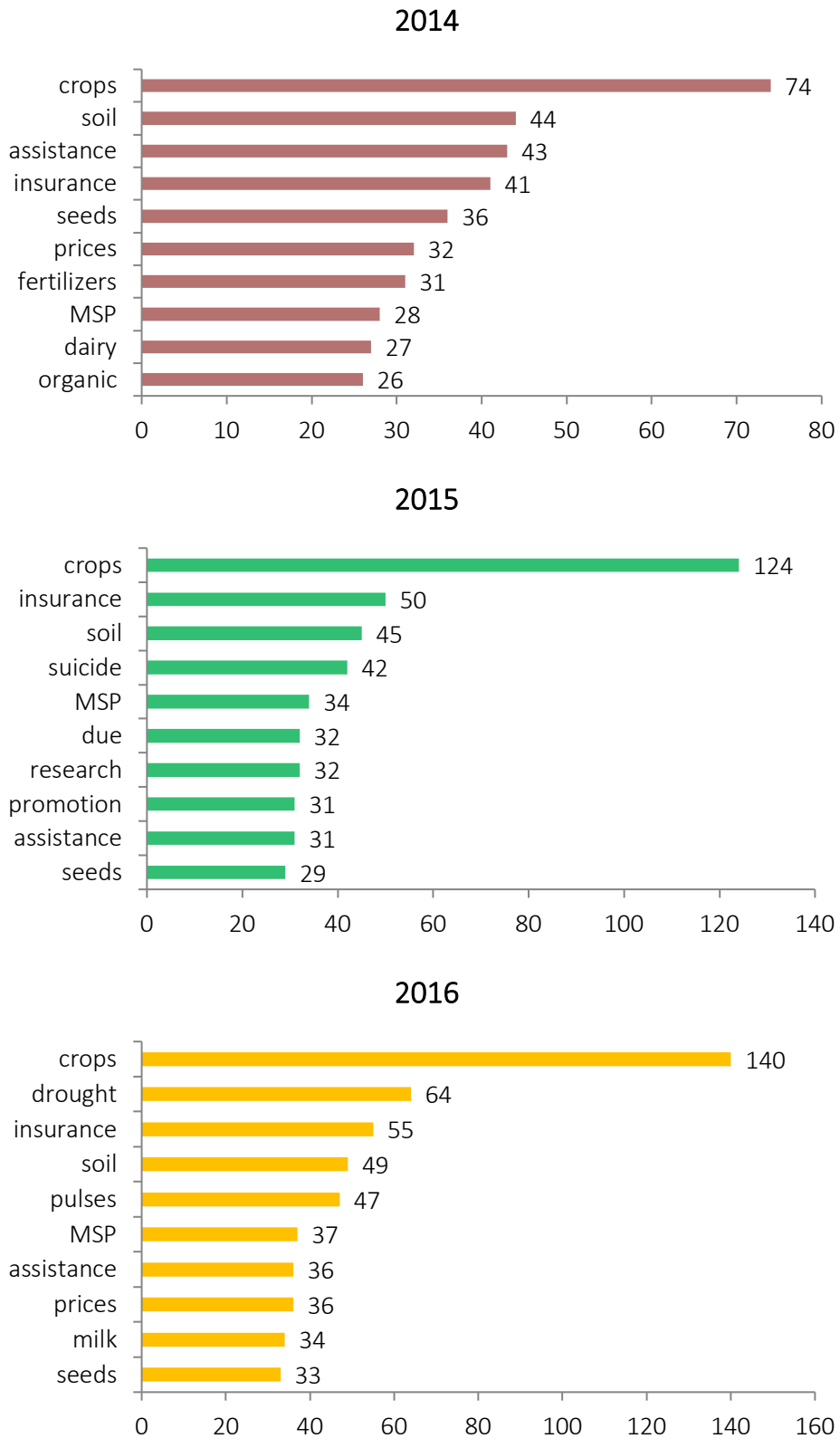
The analysis begins by extracting the most frequent words from our text corpora. As discussed earlier, we perceive this frequency as a proxy that signals major issues in the order of importance in both research and policy systems—that is, the higher the frequency, the greater the importance attached to that issue in a given domain. We begin by exploring the key issues confronting the APS, and dissect them further into annual frequencies. This not only helps to focus on issues that are recurrent and hence remain unsolved over the years, but also allows one to observe new issues emerging over time. The 10 most frequent words that surfaced in the parliamentary questions on agriculture during 2014–2018, along with their frequencies, are displayed in Figure 7, and the annual frequency breakdowns are shown in Figure 8.

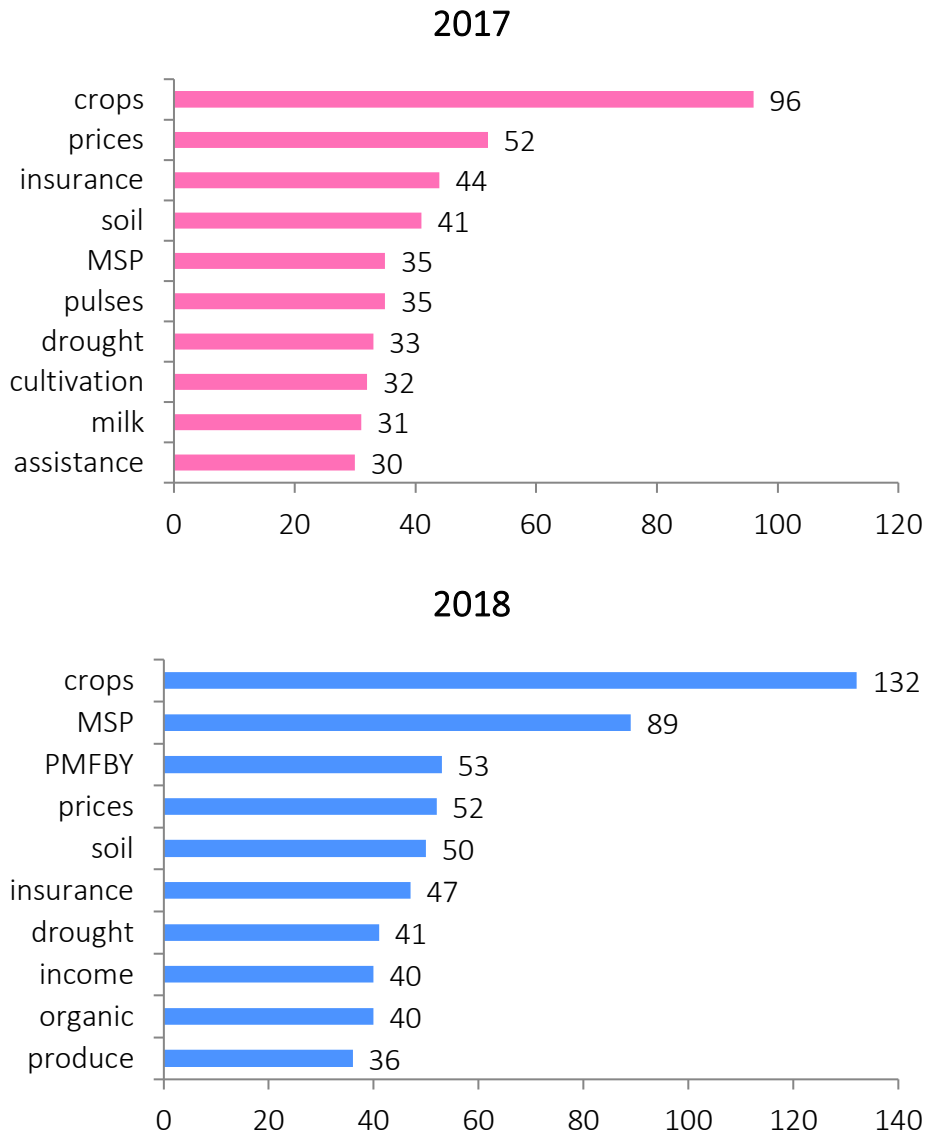
Figure 7. Key issues in India's agricultural policy system, 2014–2018



Source: Authors.
Note: MSP = minimum support price.

Figure 8. Persistence and deviations in agricultural policy issues, 2014–2018





Source: Authors.
Note: MSP = minimum support price; PMFBY = pradhan mantri fasal bima yojana, a government crop insurance program for farmers.

In general, we could observe these 10 major issues (word frequencies) to fall under two clusters, one that reflects distress-related factors in agriculture and the corresponding demands from the farm sector, and another that indicates productivity- and income-enhancing channels. These two clusters are similar to the two sides of a coin. For instance, the minimum support price (MSP), prices, and assistance are prominent demands from the agrarian class over the years as a safety net against natural disasters (such as drought) and other risks they face in farming, and insurance is the means to mitigate such risk. But, on the other hand, organic agriculture, pulses, and seeds are correlated with income-enhancing strategies. Annual frequencies (Figure 8) validate this argument. The words *MSP* and *insurance* reappeared in all five years studied, *prices* and *assistance* appeared in four out of five years, and *drought* appeared in three years among the top-10 category. In contrast, the words *income* and *dairy* appeared just once, and *milk* and *organic* twice. The word frequencies signal establishes the dominance of distress-related deliberations, and the annual

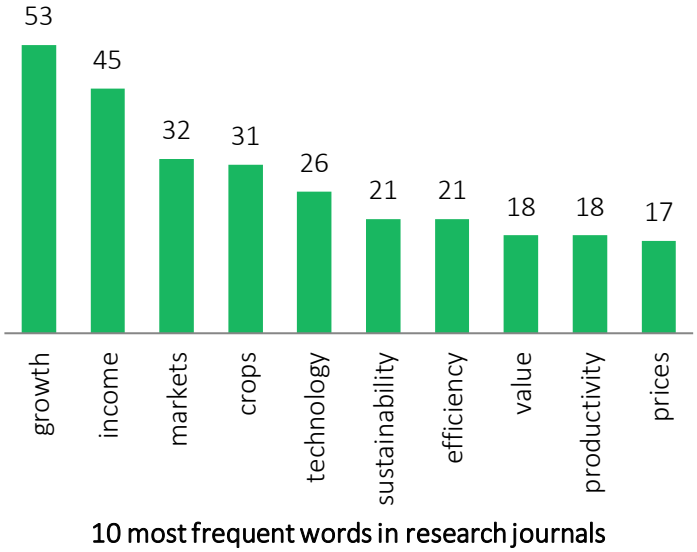
similarity points toward the persistence of issues over time. After all, *crops* were the most cared-about category, standing at the highest word frequency every year.

But the dominance of agrarian woes in both the houses doesn't subdue the APS's efforts to promote income and growth. The appearance of *soil* in all five years and *seeds* in three out of five years demonstrates the policy system's consistent efforts to promote sustainable agriculture while promoting income and growth (mentions of soil are related to testing soil health). Words concerning profitable agriculture practices appear with lower frequency in a relative sense but are not entirely absent from the top-10 word list. In fact, one would consider these income-augmenting strategies as the means that address agrarian woes by integrating farmers into profitable value chains and hence helping them realize higher prices.

Focus Areas in India's Agroeconomic Research System

It is pertinent from Figure 9 that there is an exact overlap in the issues raised by the AERS and the issues confronting the APS. For instance, whereas the APS was faced with solving agrarian woes during the study years, the AERS looked at means to address these woes. Growth promotion and income augmentation (represented by the words *growth* and *income*) had always been the solutions for agrarian sufferings, and those are the areas researched by the AERS as well, as reflected in the first two highest-frequency words.

Figure 9. Key issues in the agroeconomic research system, 2014–2018



Source: Authors.

The AERS has also addressed both the ends and the means of profitable and sustainable agriculture. Subsequent word frequencies convey the instruments with which these ends are to be attained while also sustaining resources for the future. *Markets* and *technology* are the primary channels for farmers to earn a higher income. Whereas technology enhances *productivity*, *efficiency* warrants *sustainability* in the food system. These were the aspects on which emphasis was laid. Thus, one sees the multidimensional research subjects of the AERS, reflecting a holistic approach.

The Research-Policy Nexus

The above discussions demonstrate that there exists remarkable synergy between the research and policy systems. While this serves, to a greater extent, the purpose of the present study, it also leaves specific issues untouched. For instance, the observation that agrarian woes predominate in the parliamentary deliberations undermines the efforts put forth by the bureaucracy, the political system, and the government, as well as the contributions made by the research system over the years since its establishment. This effect could be because of comparisons made earlier with just a few "most frequent" words and because we ourselves classified the issues under specific categories—that is, there is a possibility of subjectivity bias. To enhance our understanding further, we attempted to expand the horizon of both systems under study and classify key issues under different clusters. Of note, unlike earlier, when we ourselves performed the classification, the LDA technique processes the questions and articles, identifies key issues, and automates classification under some latent topics based on probability principles. Hence, the process involves no subjectivity claims and avoids the "common sense" ideology frequently attached to the public policy literature.

Table 2. Latent Dirichlet allocation results

Agricultural policy system					
Cluster 1	**Probability**	**Cluster 2**	**Probability**	**Cluster 3**	**Probability**
Crops	0.08667	Prices	0.03112	Soil	0.03904
Insurance	0.03675	MSP	0.02669	Research	0.01910
Drought	0.02945	Seeds	0.02276	Income	0.01570
Assistance	0.02266	Pulses	0.02190	Organic	0.01480
Suicide	0.01703	Milk	0.02175	Fishing	0.01294
Agroeconomic research system					
Cluster 1	**Probability**	**Cluster 2**	**Probability**	**Cluster 3**	**Probability**
Growth	0.02760	Markets	0.04122	Income	0.04900
Technology	0.02683	Prices	0.02193	Growth	0.02674
Efficiency	0.02288	Dairy	0.01935	Crops	0.02132
Sustainability	0.02222	Value	0.01807	Doubling	0.01423
Productivity	0.01860	Livestock	0.01382	Diversification	0.01379

Source: Authors' calculations.
Note: MSP = minimum support price.

The results broaden our view and show yet again the existence of synergy between the research and policy systems (Table 2). Under LDA, we find key issues in the parliamentary deliberations falling broadly under three dimensions. The first cluster absorbs agrarian distress, the second reflects market-based instruments and product-mix channels, and the third covers sustainable means of achieving the ends listed in the first two clusters. Better prices and higher MSP help to ease distress through market interventions, quality seed use increases production and productivity, and diversification toward milk and pulses helps to generate higher income. The third cluster reflects the role of research in income enhancement and the need for agricultural sustainability through maintaining soil health and adopting organic practices. Among the issues focused on by the research system, the first cluster covers much broader macroeconomic dimensions of agriculture—those that address growth, technology-linked productivity, and the role of efficiency in sustainability. The second cluster focuses on markets for better prices and allied sector products such as livestock and dairy, and the third cluster covers broader income-enhancing strategies.

The observations above indicate that the research and policy systems are engaged in addressing common issues, thus reflecting a mutual bidirectional flow of information exchange—a synergy. One would interpret this synergy from two perspectives. From the research system's perspective, when the policy system is concerned with solving agrarian issues, the research system focuses on income-enhancing strategies as the

means. When the policy system is encountering sustainability issues, the research system discusses relevant technology, efficiency, and productivity as the means. And when the policy system is concentrating on markets as a means for delivering better prices to farmers, the research system identifies market demands and suggested market promotion strategies. Thus, the role of the research system as a key element in practical policy making is evident. From the policy system's perspective, it could be inferred that the deliberations on income-enhancing and growth-promoting strategies necessarily take place through the use of knowledge delivered by the research system.

Although the response of the research system to policy demands and the utilization of research outputs in policy making are irrefutable, there exist certain issues to which both the research and policy systems turn their attention. The high-frequency appearance of issues such as drought and assistance, and MSP and prices, continues to raise the question of profitability in agriculture, demanding intensive care from both research and policy institutions. Given the size of marginal and smallholder communities—there were 120 million marginal and small farms during 2015–2016 (MoAFW 2019)—such issues need continuous attention. Although the research system has concentrated more on the ends, such as income and growth, and on much broader ideas such as efficiency, productivity, and technology, the means of attaining these ends should be given the spotlight. Similar is the case of concepts such as diversification, which are too large to handle due to the numerous ways of attaining them. This leads us to conclude that the domain of focus should be made still more narrow, precise, and site-specific in the AERS.

Turning toward the APS, although the role of research has been increasingly recognized, the resources delivered for upscaling research appear insufficient. Over the decades, several studies and committees have highlighted the need for higher financial resources to fund research activities (Ramasamy 1997; Evenson, Pray, and Rosegrant 1999; Alston et al. 2000; Fan, Gulati, and Thorat 2008; Pal and Byerlee 2006; Balani 2014; Pal 2017; MoF 2018). Despite the rise in absolute terms, the share of research as a percentage of agricultural gross value added still stands at an abysmal 0.24 percent.[9] One would notice strong correspondence in the second cluster under both AERS and APS, compared with the other clusters (Table 2). Given the priority of high-value sectors such as dairy, fisheries, and organic agriculture, reorienting the research focus toward those sectors would require enhanced financial support. Upscaling allocations and further intake of existing research outputs would help the APS to improve its pace of attaining social objectives.

6. Conclusions

The present study explored the nexus between the AERS and the APS in India. That is, it inquired into how far the agricultural policies and reform processes designed and executed by the bureaucracy and political system are evidence-based, and reciprocally, the degree of alignment of the research proceedings to meet the policy demands. As a novel approach, we used questions raised at two parliamentary houses, the House of the People (Lok Sabha) and the Council of States (Rajya Sabha) to the MoAFW, and filtered for key issues confronting the APS. In addition, using the list of research articles published in two major national agricultural economics journals (*Agricultural Economics Research Review* and *Indian Journal of Agricultural Economics*), we verified whether the research system had aligned itself toward addressing these policy issues. Because all of this information is contained in texts, we used machine learning techniques—tag clouds (word frequencies) and LDA—to identify key issues and automate classification, and examined the synergy between the research and policy systems.

Results showed remarkable synergy between these systems, thus invalidating the two-communities hypothesis. In fact, the research system has addressed both the ends and the means of profitable and

[9] Authors' estimates based on national-level budget for 2020–2021 (MoF 2020, MoSPI 2020).

sustainable agriculture. The LDA results broadened our understanding of the synergy between these systems. When the policy system is concerned with solving agrarian issues, the research system focuses on income-enhancing strategies as the means. When the policy system is encountering sustainability issues, the research system discusses relevant technology, efficiency, and productivity as the means. And when the policy system is concentrating on markets as a means for delivering better prices to farmers, the research system identifies market demands and suggests market promotion strategies. Thus, the role of the research system in practical policy making is evident. From the policy systems perspective, it could be inferred that deliberations on income-enhancing and growth-promoting strategies take place essentially through the use of research knowledge delivered by the research system.

The study identified certain issues on which both the research and policy systems should concentrate further. The high-frequency appearance of issues such as drought, assistance, the MSP, and prices over the years continues to raise the question of profitability in agriculture, demanding intensive care from both research and policy institutions. Given the size of marginal and smallholder communities, such issues need continuous attention. Though the research system has concentrated more on the ends, such as income and growth, and on much broader ideas such as efficiency, productivity, and technology, the means of attaining these ends must be given greater focus. Similar is the case with concepts such as diversification. These findings lead the study to conclude that the focus of agricultural research should be made still more narrow, precise, and site-specific. Turning toward APS, although the role of research has been recognized, the resources delivered for upscaling research appear insufficient. Our calculations show that research intensity stood at 0.24 percent during 2019–2020. Upscaling of allocations and further intake of existing research outputs would help the APS to enhance its pace of attaining social objectives.

REFERENCES

Aldous, P. D. J. 1983. "Exchangeability and Related Topics." In *École d'Été de Probabilités de Saint-Flour* 14:1–198. https://www.springer.com/gp/book/9783540152033.

Alston, J. M., C. Chan-Kang, M. C. Marra, P. G. Pardey, and T. J. Wyatt. 2000. *A Meta-analysis of Rates of Return to Agricultural R&D: Ex Pede Herculem?* Research Report 113. Washington, DC: International Food Policy Research Institute.

Anheier, H. K. 2019. "On the Future of the Public Policy School." *Global Policy* 10 (1): 75–83. https://doi.org/10.1111/1758-5899.12599.

Ashrafian, H., and A. Darzi. 2018. "Transforming Health Policy through Machine Learning." *PLoS Medicine* 15 (11): e1002692. https://doi.org/10.1371/journal.pmed.1002692.

Bader, V., and S. Kaiser. 2019. "Algorithmic Decision-Making? The User Interface and Its Role for Human Involvement in Decisions Supported by Artificial Intelligence." *Organization* 26 (5): 655–672. https://doi.org/10.1177/1350508419855714.

Balani, S. 2014. *Standing Committee Report Summary: An Evaluation of the National Agricultural Research System*. PRS Legislative Research. New Delhi: Institute for Policy Research Studies. https://www.prsindia.org/sites/default/files/parliament_or_policy_pdfs/1395895547--SCR%20Summary-%20National%20Agricultural%20Research%20System.pdf.

Banks, G. 2015. "Could Academic Research Be More Policy Influential?" *Public Administration Review* 76 (1): 33–34. https://doi.org/10.1111/puar.12482.

Bansak, K., J. Ferwerda, J. Hainmueller, A. Dillon, D. Hangartner, D. Lawrence, and J. Weinstein. 2018. "Improving Refugee Integration through Data-Driven Algorithmic Assignment." *Science* 359:325–329.

Biamonte, J., P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd. 2017. "Quantum Machine Learning." *Nature* 549:195–202. https://doi.org/10.1038/nature23474.

Black, N. 2001. "Evidence Based Policy: Proceed with Care." *BMJ* 323 (7307): 275–279. https://doi.org/10.1136/bmj.323.7307.275.

Blei, D. M., and J. D. Lafferty. 2007. "A Correlated Topic Model of *Science*." *The Annals of Applied Statistics* 1 (1): 17–35. https://doi.org/10.1214/07-aoas114.

Blei, D. M., A. Y. Ng, and M. I. Jordan. 2003. "Latent Dirichlet Allocation." *Journal of Machine Learning Research* 3:993–1022. https://www.jmlr.org/papers/volume3/blei03a/blei03a.pdf.

Bremer, S. 2017. "Have We Given Up Too Much? On Yielding Climate Representation to Experts." *Futures* 91:72–75. https://doi.org/10.1016/j.futures.2017.01.008.

Bzdok, D., N. Altman, and M. Krzywinski. 2018. "Statistics versus Machine Learning." *Nature Methods*, 15:233–234. https://doi.org/10.1038/nmeth.4642.

Cao, L., A. Gurevich, K. L. Alexander, C. B. Naman, T. Leão, E. Glukhov, T. Luzzatto-Knaan, F. Vargas, R. Quinn, A. Bouslimani, L. F. Nothias, N. K. Singh, J. G. Sanders, R. A. S. Benitez, L. R. Thompson, Md-N. Hamid, J. T. Morton, A. Mikheenko, A. Shlemov, A. Korobeynikov, I. Friedberg, R. Knight, K. Venkateswaran, W. H. Gerwick, L. Gerwick, P. C. Dorrestein, P. A. Pevzner, and H. Mohimani. 2019. "MetaMiner: A Scalable Peptidogenomics Approach for Discovery of Ribosomal Peptide Natural Products with Blind Modifications from Microbial Communities." *Cell Systems* 9 (6): 600–608.e4. https://doi.org/10.1016/j.cels.2019.09.004.

Caplan, N. 1979. "The Two-Communities Theory and Knowledge Utilization." *American Behavioral Scientist* 22 (3): 459–470. https://doi.org/10.1177/000276427902200308.

Cheng, H.-F., R. Wang, Z. Zhang, F. O'Connell, T. Gray, F. M. Harper, and H. Zhu. 2019. "Explaining Decision-Making Algorithms through UI: Strategies to Help Non-expert Stakeholders." In *CHI '19: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–12. New York: Association for Computing Machinery. https://doi.org/10.1145/3290605.3300789.

de Finetti, B. 1990. *Theory of Probability.* Vols. 1–2. Chichester, UK: Wiley.

Deerwester, S., S. T. Dumais, G. W. Furnas, T. K. Landauer, and R. Harshman. 1990. "Indexing by Latent Semantic Analysis." *Journal of the American Society for Information Science* 41 (6): 391–407.

https://asistdl.onlinelibrary.wiley.com/doi/10.1002/(SICI)1097-4571(199009)41:6%3C391::AID-ASI1%3E3.0.CO;2-9.

Department of Animal Husbandry and Dairying. 2020. "About the Department." Ministry of Fisheries, Animal Husbandry and Dairying. Accessed 06 11. http://dadf.gov.in/about-us/about-department.

Department of Fisheries. 2020. "About the Department." Ministry of Fisheries, Animal Husbandry and Dairying, Government of India. Accessed 06 11. http://dof.gov.in/about-us/about-department.

Desmarais, B. A., and J. A. Hird. 2014. "Public Policy's Bibliography: The Use of Research in US Regulatory Impact Analyses." *Regulation and Governance* 8:497–510. https://doi.org/10.1111/rego.12041.

Dumais, S. T., G. W. Furnas, T. K. Landauer, S. Deerwester, and R. Harshman. 1988. "Using Latent Semantic Analysis to Improve Access to Textual Information." In *CHI '88: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 281–285. New York: Association for Computing Machinery. https://doi.org/10.1145/57167.57214.

Dunn, W. N. 1980. "The Two-Communities Metaphor and Models of Knowledge Use: An Exploratory Case Survey." *Science Communication* 1 (4): 515–536. https://doi.org/10.1177/107554708000100403.

Evenson, R. E., C. E. Pray, and M. W. Rosegrant. 1999. *Agricultural Research and Productivity Growth in India*. Research Report 109. Washington, DC: International Food Policy Research Institute. https://www.ifpri.org/publication/agricultural-research-and-productivity-growth-india.

Fan, S., A. Gulati, and S. Thorat. 2008. "Investment, Subsidies, and Pro-poor Growth in Rural India." *Agricultural Economics* 39:163–170. https://doi.org/10.1111/j.1574-0862.2008.00328.x.

Glaeser, E. L., A. Hillis, S. D. Kominers, and M. Luca. 2016. "Crowdsourcing City Government: Using Tournaments to Improve Inspection Accuracy." *American Economic Review: Papers & Proceedings* 106 (5): 114–118. https://doi.org/10.1257/aer.p20161027.

Hofmann, T. 1999. "Probabilistic Latent Semantic Analysis." In *Proceedings of the Twenty-Second Annual International SIGIR Conference on Research and Development in Information Retrieval*, 50–57. New York: Association for Computing Machinery. https://doi.org/10.1145/312624.312649.

Hong, L., J. Lin, S. Li, F. Wan, H. Yang, T. Jiang, D. Zhao, and J. Zeng. 2020. "A Novel Machine Learning Framework for Automated Biomedical Relation Extraction from Large-Scale Literature Repositories." *Nature Machine Intelligence* 2:347–355. https://doi.org/10.1038/s42256-020-0189-y.

ICAR (Indian Council of Agricultural Research). 2020. ICAR Personnel Management System. Ministry of Agriculture and Farmers' Welfare. https://pms.icar.gov.in/.

Jones, K. S. 1972. "A Statistical Interpretation of Term Specificity and Its Application in Retrieval." *Journal of Documentation* 28 (1): 11–21. https://doi.org/10.1108/eb026526.

Jørgensen, M. B. 2011. "Understanding the Research-Policy Nexus in Denmark and Sweden: The Field of Migration and Integration." *British Journal of Politics and International Relations* 13:93–109. https://doi.org/10.1111/j.1467-856X.2010.00441.x.

Kattumuri, R. 2015. "Evidence and the Policy Process from an Indian Perspective." *Contemporary Social Science* 10 (2): 191–201. https://doi.org/10.1080/21582041.2015.1056749.

Kleinberg, J., H. Lakkaraju, J. Leskovec, J. Ludwig, and S. Mullainathan. 2018. "Human Decisions and Machine Predictions." *The Quarterly Journal of Economics* 133 (1): 237–293. https://doi.org/10.1093/qje/qjx032.

Kovacic, Z. 2017. "Investigating Science for Governance through the Lenses of Complexity." *Futures* 91:80–83. https://doi.org/10.1016/j.futures.2017.01.007.

Kovacic, Z., and M. Giampietro. 2015. "Empty Promises or Promising Futures? The Case of Smart Grids." *Energy* 93:67–74. https://doi.org/10.1016/j.energy.2015.08.116.

La Brooy, C., and M. Kelaher. 2017. "The Research-Policy-Deliberation Nexus: A Case Study Approach." *Health Research Policy and Systems* 15 (75): 1–10. https://doi.org/10.1186/s12961-017-0239-z.

Luhn, H. P. 1957. "A Statistical Approach to Mechanized Encoding and Searching of Literary Information." *IBM Journal of Research and Development* 1 (4): 309–317. https://doi.org/10.1147/rd.14.0309.

MoAFW (Ministry of Agriculture and Farmers' Welfare, India). 2019. *Agriculture Census 2015–16*. New Delhi.

MoF (Ministry of Finance, India). 2018. "Transforming Science and Technology in India." In *Economic Survey 2017–18.* Vol. 1. 119–130. New Delhi.

———. 2020. *Union Budget 2020–21*. New Delhi.

Mohimani, H., R. D. Kersten, W. T. Liu, M. Wang, S. O. Purvine, S. Wu, H. M. Brewer, L. Pasa-Tolic, N. Bandeira, B. S. Moore, P. A. Pevzner, and P. C. Dorrestein. 2014. "Automated Genome Mining of Ribosomal Peptide Natural Products." *ACS Chemical Biology* 9 (7): 1545–1551. https://doi.org/10.1021/cb500199h.

MoSPI (Ministry of Statistics and Programme Implementation, India). 2020. *Press Note on Provisional Estimates of Annual National Income 2019–2020 and Quarterly Estimates of Gross Domestic Product for the Fourth Quarter (Q4) of 2019–20.* New Delhi.

Newman, J., A. Cherney, and B. W. Head. 2015. "Do Policy Makers Use Academic Research? Reexamining the 'Two Communities' Theory of Research Utilization." *Public Administration Review* 76 (1): 24–32. https://doi.org/10.1111/puar.12464.

Newson, R., L. King, L. Rychetnik, A. E. Bauman, S. Redman, A. J. Milat, J. Schroeder, G. Cohen, and S. Chapman. 2015. "A Mixed Methods Study of the Factors That Influence Whether Intervention Research Has Policy and Practice Impacts: Perceptions of Australian Researchers." *BMJ Open* 5(e008153):1–13. https://doi.org/10.1136/bmjopen-2015-008153.

Nutley, S., I. Walter, and H. T. O. Davies. 2007. *Using Evidence: How Research Can Inform Public Services*. Bristol, UK: Policy Press.

Obermeyer, Z., and S. Mullainathan. 2019. "Dissecting Racial Bias in an Algorithm That Guides Health Decisions for 70 Million People." In *Proceedings of FAT* '19: Conference on Fairness, Accountability, and Transparency, Atlanta, GA, USA, January 29–31, 2019*, 89. New York: Association for Computing Machinery. https://doi.org/10.1145/3287560.3287593.

Pal, S., ed. 2017. *Agricultural R&D Policy in India: The Funding, Institutions and Impact*. New Delhi: Indian Council of Agricultural Research–National Institute of Agricultural Economics and Policy Research.

Pal, S., and D. Byerlee. 2006. "India: The Funding and Organization of Agricultural R&D—Evolution and Emerging Policy Issues." In *Agricultural R&D Policy in the Developing World: Too Little, Too Late,* edited by P. G. Pardey, J. M. Alston, and R. R. Piggot, 155–193. Washington, DC: International Food Policy Research Institute.

Parliament of India, Council of States. 2019. Question Search database. Accessed 02 20. https://rajyasabha.nic.in/rsnew/Questions/Search_minwise.aspx.

Parliament of India, House of the People. 2019. Questions Search database. Accessed 02 20. http://loksabhaph.nic.in/Questions/Qtextsearch.aspx.

Perche, D. 2011. "Dialogue between Past and Present: Policy Evaluation and History." *Australian Journal of Politics and History* 57 (3): 403–419. https://doi.org/10.1111/j.1467-8497.2011.01605.x.

Ramasamy, C. 1997. "Return to Research Investment in Agriculture." In *Proceedings of International Workshop on Integrating Research Evaluation Efforts*, edited by M. C. S. Bantilan and P. K. Joshi. Patancheru, India: International Crops Research Institute for the Semi-arid Tropics.

Saltelli, A. 2020. "Ethics of Quantification or Quantification of Ethics?" *Futures* 116:1–11. https://doi.org/10.1016/j.futures.2019.102509.

Saltelli, A., and M. Giampietro. 2017. "What Is Wrong with Evidence Based Policy, and How Can It be Improved?" *Futures* 91:62–71. https://doi.org/10.1016/j.futures.2016.11.012.

Sareen, S., A. Saltelli, and K. Rommetveit. 2020. "Ethics of Quantification: Illumination, Obfuscation and Performative Legitimation." *Palgrave Communications* 6 (20): 1–5. https://doi.org/10.1057/s41599-020-0396-5.

Smith, A. 2018. *Public Attitudes toward Computer Algorithms*. Washington, DC: Pew Research Center.

Stads, G.-J., K. Sastry, G. Kumar, T. Kondisetty, and L. Gao. 2016. *Agricultural R&D Indicators Factsheet.* Washington, DC and Hyderabad, India: International Food Policy Research Institute and National Academy of Agricultural Research Management.

Stokes, J. M., K. Yang, K. Swanson, W. Jin, A. Cubillos-Ruiz, N. M. Donghia, C. R. MacNair, S. French, L. A. Carfrae, Z. Bloom-Ackermann, V. M. Tran, A. Chiappino-Pepe, A. H. Badran, I. W. Andrews, E. J. Chory, G. M. Church, E. D. Brown, T. S. Jaakkola, R. Barzilay, and J. J. Collins. 2020. "A Deep Learning Approach to Antibiotic Discovery." *Cell* 180 (4): 688–702.e13. https://doi.org/10.1016/j.cell.2020.01.021.

Venghaus, S., and J. F. Hake. 2018. "Nexus Thinking in Current EU Policies: The Interdependencies among Food, Energy and Water Resources." *Environmental Science and Policy* 90:183–192. https://doi.org/10.1016/j.envsci.2017.12.014.

Zerilli, J., A. Knott, J. Maclaurin, and C. Gavaghan. 2019. "Algorithmic Decision-Making and the Control Problem." *Minds and Machines* 29:555–578. https://doi.org/10.1007/s11023-019-09513-7.

Zhong, M., K. Tran, Y. Min, C. Wang, Z. Wang, C. T. Dinh, P. De Luna, Z. Yu, A. S. Rasouli, P. Brodersen, S. Sun, O. Voznyy, C.-S. Tan, M. Askerka, F. Che, M. Liu, A. Seifitokaldani, Y. Pang, S.-C. Lo, A. Ip, Z. Ulissi, and E. H. Sargent. 2020. "Accelerated Discovery of CO_2 Electrocatalysts Using Active Machine Learning." *Nature* 581:178–183. https://doi.org/10.1038/s41586-020-2242-8.

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