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Labour-saving technologies in smallholder agriculture: An economy-wide model with field operations

Arndt Feuerbacher[1] | **Jonas Luckmann**[2]

[1]Institute of Agricultural Policy and Markets, Ecological and Economic Policy Modelling Group, University of Hohenheim, Stuttgart, Germany

[2]International Agricultural Trade and Development Group, Humboldt-Universität zu Berlin, Berlin, Germany

Correspondence
Arndt Feuerbacher, Institute of Agricultural Policy and Markets, Ecological and Economic Policy Modelling Group, Schwerzstr. 46, 70599 Stuttgart, Germany.
Email: a.feuerbacher@uni-hohenheim.de

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Abstract

Labour-saving technologies are relevant for agricultural development. Yet, as this study shows, they are poorly integrated into agricultural production functions of economy-wide models. We report a computable general equilibrium (CGE) model, which explicitly incorporating field operations (e.g. land preparation, weeding or harvesting) in the context of smallholder agriculture. The field operations approach allows to model technological trade-offs in organic and conventional production systems at various stages of the agricultural production process. Simulating a structural change scenario, we compare the performance of the field operations approach with published benchmark production structures by assessing how they replicate empirically observed changes in land and agrochemical use. This benchmark analysis shows that incorporating field operations replicates the observed empirical changes most accurately and allows for more realistic modelling of labour-saving technologies. We use the field operations model to investigate three policy options to mitigate labour shortages in the agricultural sector of Bhutan. Permitting the employment of Indian workers in agriculture has the highest short-term potential in this respect. We find that subsidising agricultural machinery hiring services and removing import tariffs on agrochemical inputs are found to be less effective. Further options for model developments, such as combining field operations and labour market seasonality, are highlighted.

KEYWORDS

applied general equilibrium, baseline forecasting, constant elasticity of substitution, economic modelling, Leontief technology, model validation

Feuerbacher and Luckmann have contributted equally to this paper

JEL CLASSIFICATION
C68, J43, Q10

1 | INTRODUCTION

Historically, most economies have pursued development trajectories through which growth in the secondary and tertiary sectors was accompanied by the primary sector releasing surplus labour (Christiaensen & Martin, 2018; Gollin, 2014). Once surplus labour is no longer available, i.e. the Lewis turning point is reached, the agricultural sector has to increase its productivity to release labour to the rest of the economy (Lewis, 1954; McMillan et al., 2014). The challenge of increasing agricultural productivity is usually addressed by land- and labour-saving technologies, specifically through the adoption of, *inter alia*, high-yielding crop varieties, chemical fertilisers, farm machinery, and pesticides (Gallardo & Sauer, 2018). These have been the main ingredients of modern agricultural development, particularly during the era of the Green Revolution (Conway & Barbier, 2013), and have led to a strong reduction in agricultural employment (Collier & Dercon, 2014). These features of economic transformation are of high relevance for policy analysis in the context of low-income countries, where a large share of the population's livelihood still relies on agriculture.

Agriculture and especially plant production is subject to biophysical processes (weather, soil fertility, the occurrence of pests, etc.) and farmers' decisions (on the production system, crop choice, time of planting, quantities of fertiliser applied, etc.). Plant production follows a crop calendar, which determines the respective field operations (from seeding to harvesting) and their sequence (Antle, 1983; Jagnani et al., 2021). The complexity of agricultural production systems especially manifests in low-income countries in the tropics and subtropics, where the agricultural sector accounts for a high share of GDP and employment while being characterised by high labour intensity and small landholdings (Frija et al., 2020). The adoption of labour-saving technologies in smallholder farming is a continuous process and often only concerns selective stages of the agricultural production process. The use of power tillers, for instance, lessens the labour requirement for land preparation, but other field operations, such as planting, weeding and harvesting, may remain unaffected. The introduction of herbicides or the adoption of genetically modified organisms may, for instance, solely reduce the labour needed for weeding.

The impacts of structural (Bekkers et al., 2021; Mulanda Mulanda & Punt, 2021), policy (Dixon & Rimmer, 2022) or technological change (Wittwer & Banerjee, 2015) on the agricultural sector and the economy as a whole are commonly assessed using economy-wide simulation models, such as computable general equilibrium (CGE) models. However, such models fail to adequately depict the features of smallholder systems, particularly regarding the role of labour (Dixon & Jorgenson, 2012). In reviewing the literature, we show that economy-wide models often incorporate a rather simplistic production structure, which does not allow us to model the realistic potential of labour-saving technologies. We report an alternative and novel production structure that incorporates field operations and thus permits us to model technological trade-offs at various stages of the agricultural production process. We demonstrate that this approach allows for a better fit with empirically observed changes in the agricultural system.

We use Bhutan as a case study, where the agricultural sector employs approximately 50% of the labour force (Ministry of Labour and Human Resources, 2019). Cropping systems in Bhutan are characterised by small-scale production, high labour intensity and a low use of agrochemicals. Thus, the predominant production system can be called 'organic by default' (for brevity, we refer to only 'organic' henceforth). This has led policymakers to suggest that the agricultural sector should become 100% organic (Feuerbacher et al., 2018). However, due to increasing levels of urbanisation, rural labour shortages are becoming an urgent challenge for farmers in Bhutan (MoAF, 2013a, 2019a).

The contributions of this study are twofold. First, we compare the field operations model to commonly used model approaches based on a comprehensive literature review. We simulate a reference scenario to model the structural change in Bhutan's economy and labour force between 2012 and 2018. In this period, the agricultural labour force decreased by 5.9%. We demonstrate that the field operations model outperforms the benchmark approaches in replicating empirically observed changes in land and agrochemical use. Such rigorous comparisons of production structures are rather scarce in the literature but highly relevant to assess the value-added and superiority of method development. The second contribution comprises an analysis of three different policy responses that aim to mitigate labour shortages within the agricultural sector. These policies are simulated using the novel field operations model approach calibrated to empirical changes in land and agrochemical use.

The remainder of this paper is structured as follows: Section 2 gives an overview of commonly used approaches depicting agricultural production in CGE models. Section 3 introduces the field operations model and database as well as the model benchmark approach. Section 4 introduces the reference scenario representing the structural change observed in the Bhutanese economy in recent years and three policy scenarios to mitigate labour shortages in the agricultural sector. In Section 5, the outcomes of the different model set-ups are compared and the results of the policy scenarios for Bhutan are presented. In section 6 we discuss the modelling approach's capability, further model development options and policy implications. Conclusions are presented in Section 7.

2 | AGRICULTURAL PRODUCTION STRUCTURES IN ECONOMY-WIDE MODELS

In CGE models, the production structure of activities is described as a 'technology tree' consisting of a series of nested constant elasticity of substitution (CES) production functions or fixed share aggregates (i.e. following the Leontief assumption). The underlying assumptions are constant returns to scale and separability, meaning that the marginal rate of substitution between inputs aggregated in one nest is independent of the quantity of any other inputs used. However, the structure of the 'technology tree' is rarely empirically founded and thus is often determined by researchers' intuition (Simola, 2015).

Most standard models apply simple two- to three-stage CES nesting, whereby the top-level aggregate intermediate inputs are combined with total value-added (Figure 1). At the level below, on the one hand, value-added is composed of production factors and usually labour, capital and land. On the other hand, commodities are aggregated to form intermediate input.

There is no consensus on when production nests should assume CES or Leontief technology. However, most models assume (imperfect) substitution between value-added and aggregated intermediate inputs as well as between single production factors, for example, the GTAP model (Hertel, 1997). Intermediate inputs are often aggregated in fixed shares, assuming no adaptation towards a relative price change in commodities, for example in the IFPRI standard model (Lofgren et al., 2002) or in STAGE v.2 (McDonald & Thierfelder, 2015). This means, for example, that a farmer always needs to purchase a similar quantity of seeds to produce a certain quantity of crops, that is seeds cannot be substituted by other inputs. This assumption is relaxed with the GTAP-AGR, which also allows for substitution between purchased agricultural inputs (Keeney & Hertel, 2005).

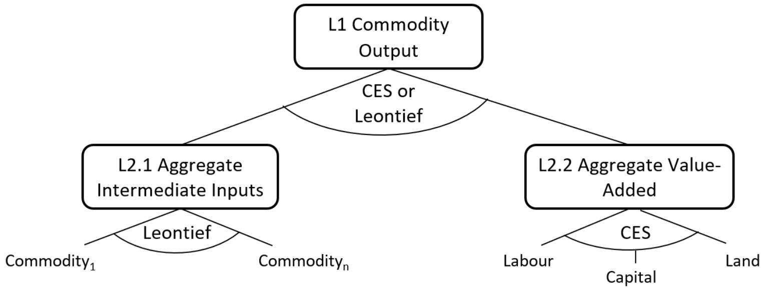

FIGURE 1 Production structure in a standard CGE model (*Source*: Adapted from Lofgren et al., 2002 p. 9)

This simple production structure is widely applicable, as it requires a limited amount of data for parameterisation. However, this approach can be criticised for its oversimplifications and crude assumptions, which might lead to unrealistic results, especially regarding effects occurring at the microlevel scale. Therefore, in the literature, the production structure has been expanded by adding further nests, for example, to distinguish labour categories of different degrees of substitutability (McDonald & Thierfelder, 2009).

Some research focusses especially on the production structure in the agricultural sector given its relevance to the use of land and water resources and its contribution to GDP, employment and livelihoods in many countries. In addition, as pointed out above, the many technological trade-offs involved make the agricultural production system quite complex. Some studies with a focus on the agricultural sector move intermediate inputs such as fertiliser, agrochemicals, or feedstuff to the value-added side within the production nest to allow for an adjustment of production intensity (e.g. Argüello & Valderrama-Gonzalez, 2015; Jiménez et al., 2021). The same has been done for draught animal ploughing services as a product coupled with livestock production (Holden et al., 2005) and through the integration of irrigation water from different sources (e.g. Luckmann et al., 2014). The GTAP-AGR model links the livestock sector more closely to the cropping sector by introducing a subnest under the intermediate input composite to differentiate feedstuffs, which are more easily substitutable from nonfeedstuff inputs (Keeney & Hertel, 2005).

Osman et al. (2016) use a subannual time dimension by introducing seasonal cropping activities and season-specific water supply. Dixon and Rimmer (2021) solve their model in quarterly time steps to model seasonality in the agricultural sector, and Feuerbacher et al. (2020) model seasonal labour markets by integrating the monthly labour demand of agricultural activities within the production structure. Kuiper (2005) develops a village-level CGE model with a detailed agricultural production structure accounting for (imperfect) substitution between chemical and organic fertiliser (manure), between animal and tractor ploughing and between labour and chemical plant protection (PP). This approach, however, still treats labour as a single production input with only one direct substitution relationship within the production structure. Hence, the approach does not consider the diversity of substitution relationships and technological choices that allow to reduce labour intensity. Chemical fertiliser can replace manure, and it requires less labour for application due to the higher nutrient density. This labour saving potential is not reflected in the approach used by Kuiper (2005). The same holds for the relationship between tractor and labour-intensive animal ploughing.

Despite the described developments in the production structure of the agricultural sector, many recent studies with a focus on agriculture employ standard production structures. For example, the standard IFPRI production structure is used by Benfica et al. (2019) to investigate the implications of an agricultural investment plan in Mozambique and by Mulanda Mulanda and Punt (2021) to analyse changes in transaction costs and capital availability in the Zambian agricultural sector.

3 | METHOD AND DATA

3.1 | Model

The CGE model adapted for this study is a single-country, comparative-static CGE model mainly developed from STAGE v.2 (McDonald & Thierfelder, 2015) and STAGE-DEV models (Aragie et al., 2016). We modify the model's production system to incorporate the field operations of cropping activities. In the following, we refer to this model set-up as '*fieldops*'. To adequately assess the merits of this model development, we compare the *fieldops* set-up to two *benchmark* model set-ups that reflect commonly applied production structures in economy-wide modelling (see Section 3.2). Except for differences in the production system, simulations with the *fieldops* and *benchmark* set-ups otherwise rely on identical model parameters (see Appendix A).

The agents in the model are production activities, households, incorporated enterprises, the government and the capital market. We model households' demand behaviour (the demand system) as a two-level LES-CES nest. The LES level is the linear expenditure system derived from Stone–Geary utility functions assuming utility-maximising behaviour. At this level, households determine the optimum consumption levels of aggregate commodities. At the CES level, households choose welfare-maximising combinations of 'natural' commodities subject to relative commodity prices and the constraints of preferences, income, available labour resources and subsistence requirements. This set-up allows households to substitute similar goods and services, for example rice, maize and other cereals. The income elasticities of demand for commodity groups at the LES level were estimated using cross-sectional household data from the 2012 Bhutan Living Standard Survey (Feuerbacher, 2019). The CES parameters used to aggregate the commodity groups are documented in Appendix B. Details of the production system are provided below. Following the Armington (1969) insight, demand for domestically produced commodities is differentiated from imports and specified by a CES function. Domestically produced commodities are supplied to the domestic and world markets (i.e. exports) using constant elasticity of transformation (CET) functions.

3.2 | Model set-ups with production system variants

The *fieldops* and two *benchmark* model set-ups differ in their production system design as explained below. This only concerns the production system of cropping activities, while all other economic activities remain unchanged. Generally, all model set-ups are disaggregated by conventional and organic production systems, that is whether the use of agrochemicals is allowed or banned. A Cobb–Douglas function is used to aggregate the national output of conventional and organic activities.

The model set-ups are developed from the original three-level nested CES production structure of STAGE v.2. In CES production functions, the flexibility in the aggregation of inputs according to their relative prices is determined by a parameter, substitution elasticity σ (see Pauw (2003) for a comprehensive overview). This parameter can take values between 0 and infinity. If $\sigma = 0$, the production functions are identical to a Leontief technology according to which production inputs are aggregated in fixed shares. The Cobb–Douglas function represents a special case of the CES production function with a unitary substitution elasticity ($\sigma = 1$) resulting in a constant value share of inputs. The point estimates for the CES elasticities used in the three model variants are presented together with their sources in Appendix A.

3.2.1 | The benchmark set-ups

As a benchmark, we chose a CES nesting based on standard CGE models extended by a fertiliser-land nest. This reflects the approach of Argüello and Valderrama-Gonzalez (2015) and allows for more flexibility regarding the production intensity. Based on this model, we create two *benchmark* configurations: *benchmark_CES* and *benchmark_Leontief*. The only difference between them is that they aggregate value-added at level L2.2 (Figure 2a) using either CES $\left(\sigma_{L2.2} > 0\right)$ or Leontief $\left(\sigma_{L2.2} = 0\right)$ technology. We use both set-ups, as empirical studies show that labour–land substitution is imperfect, with elasticity values estimated at close to zero: for instance, Lopez (1980) reports a mean land-labour substitution elasticity of 0.113 and Hertel et al. (2016) report a substitution elasticity value for capital–land–labour for agricultural activities of 0.24. We use the latter estimate for the *benchmark_CES* set-up.

Apart from the value-added nest substitution specification at level L2.2, both benchmarks are identical. Intermediate inputs and value-added components are aggregated according to Leontief technology (level L1 in Figure 2a). Intermediate inputs are also demanded in fixed

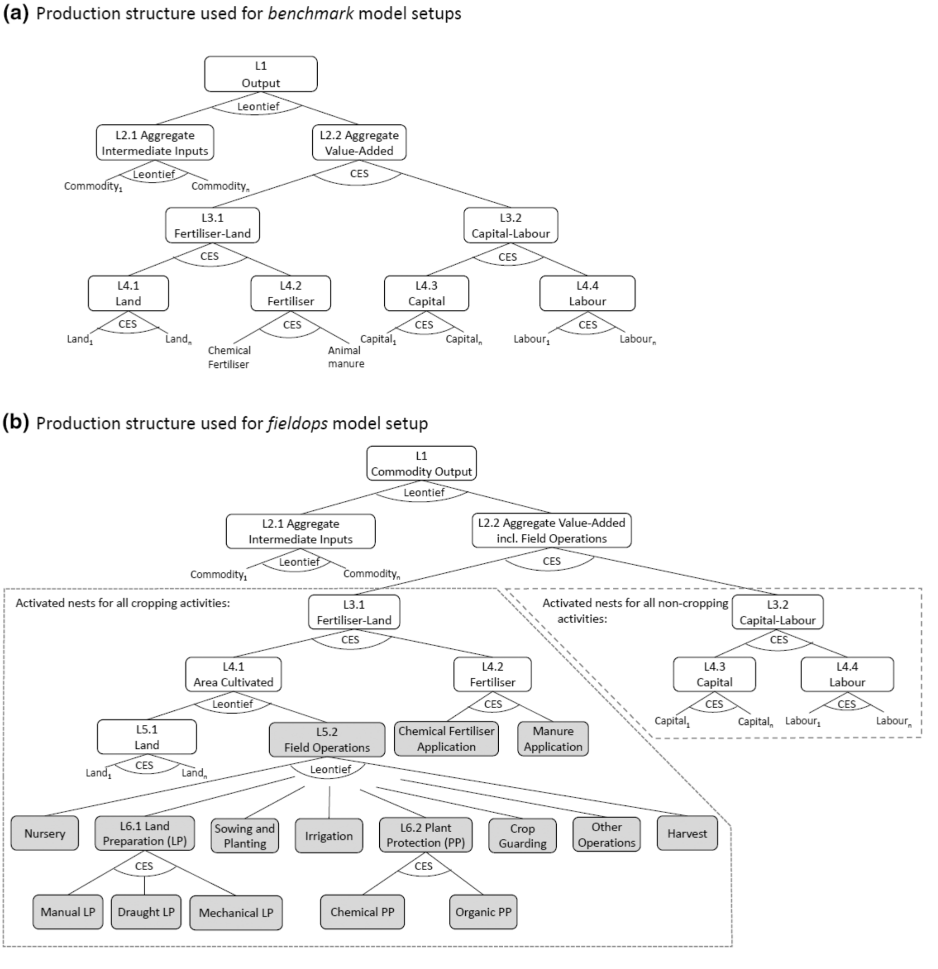

FIGURE 2 Production structure of model set-ups (*Source*: Authors' own elaboration). Note: All model set-ups distinguish between conventional and organic crop production. In organic production, there is no chemical fertiliser application nor chemical plant protection (PP). Hence, for these activities, the nests at L4.2 and L6.2 only have the respective organic input.

shares (L2.1). Intermediate inputs include all commodities except for chemical fertiliser and animal manure, which are integrated on the value-added side (see L4.2). Fertilised land (L3.1) and the capital–labour composite (L3.2) are aggregated to form total value-added at L2.2, with either CES or Leontief technology. Land (area cultivated by cropping activities) and fertilisers are aggregated using CES technology. All forms of capital (including power tillers) and labour are aggregated within the respective nests at L4.3 and L4.4. The nest at L4.1 aggregates the various land types (irrigated and rainfed land), but in this study, crops are linked to specific land types. Note: The fertiliser aggregate at L4.2 only comprises fertiliser commodities, whereas in the *fieldops* set-up, it will also include the corresponding labour needed in fertiliser application.

3.2.2 | Field operations set-up

The *fieldops* model set-up extends the production structure only for cropping activities to integrate the field operations (Figure 2b). The differences in the *benchmark* begin from L3.1 onwards, which governs the cropping activities' degree of intensification. The fertiliser aggregate at L4.2 here consists of the field operations of organic (manure) and chemical fertiliser application. These two operations differ largely in their labour requirements (see Table 1). Per unit of nutrients, organic fertilisation requires about five times more labour compared with chemical fertiliser application, as manure must be collected, stored and transported to the fields, while the nutrient density is much lower as compared to chemical fertiliser. These labour requirements for the application of organic fertilisers are not considered in the *benchmark* set-ups. We modify the nest at L4.1 to aggregate land and all remaining field operations according to Leontief technology and refer to it as 'area cultivated'. Assuming a fixed share between field operations and land is reasonable, increasing the area cultivated would also lead to a higher need for labour, which, for cropping activities, is moved from L4.4 to be included in the field operations. In addition to land preparation and PP, all field operations are directly aggregated at L5.2 using Leontief technology. At L6.1 and L6.2, the three different land preparation technologies and organic and conventional PP practices are aggregated. Note that only conventional cropping activities can substitute between organic and conventional PP.

The field operation activities themselves combine production factors and intermediate inputs as shown in Table 1. As they are noncropping activities, node L3.1 remains empty in their production structure.

3.3 | Benchmark analysis

To assess the performance of the *fieldops* model set-up, we simulate a *Reference* scenario reflecting the structural changes in Bhutan's labour market and economy occurring between 2012 (the model's base year) and 2018 with the *fieldops* and two *benchmark* model set-ups (see Section 4.1). We compare the results of each model set-up to empirical estimates of changes in land and agrochemical use. Between 2012 and 2018, the agricultural system in Bhutan generally intensified with a 10.7% drop in the overall crop area harvested. Paddy rice cultivation, the most labour-intensive crop in Bhutan with high relevance to food security and self-sufficiency, experienced a 10.6% decline. At the same time, the use of chemical fertilisers and pesticides per area increased strongly by 48.5% and 38.2% respectively.[1] Based on these four indicators, we

[1]The change in cropped area is based on MoAF (2013a, 2019a). Changes in agrochemical use are estimated via a linear trend analysis of 5-year moving averages. The annual quantities of chemical fertiliser use are taken from FAO (2020a), and uses of total pesticides are taken from COMTRADE UN (2020) and Ministry of Finance (2020).

TABLE 1 Input–output cost structure of field operations

Inputs (million Nu.[a])	Nursery	Land preparation			Sowing / Planting[c]	Fertiliser application		Other Operations	Irrigation	Plant protection		Crop Guarding[e]	Harvesting[f]
		Mechanical[b]	Draught	Manual		Organic	Chemical			Organic[d]	Chemical		
Fuel		24.5						2.4					11.3
Bulls			304.3										
Manure						194.9							
Chemical fertiliser							68.4						
Pesticides											53.5		
Labour	113.3	23.3	222.4	11.5	180.0	216.9	6.0	87.6	90.0	345.8	6.8	320.9	648.9
Capital		132.3											43.5
Total costs	**113.3**	**180.1**	**526.8**	**11.5**	**180.0**	**411.9**	**74.4**	**99.0**	**90.0**	**345.8**	**60.3**	**320.9**	**703.7**
Physical labour input (in 1000 person-days)	643	132	1263	65	1022	1232	34	497	511	1964	38	1822	3685
Nutrient use (in tons of NPK elements)						6986	954						
Use by cropping activity	Paddy rice, vegetables	All crops	All crops	All crops	All crops	All crops	Conventional cropping	Veg'es, potatoes, spices, fruits	Paddy rice, other cereals, veg'es, spices. fruits	All crops	Conventional cropping	All crops	All crops

[a]1 US$ = 53.4 Bhutanese ngultrum (Nu.).
[b]Mainly using power tillers.
[c]Incl. transplanting.
[d]Mainly manual weeding.
[e]Against wildlife.
[f]Incl. harvest machinery.

assess each model set-up's performance by calculating the normalised model error e_j of each set-up j as described in Equation 1:

$$e_j = \sum_{i=I} \left| \frac{o_i - \hat{o}_{i,j}}{o_i} \right| for\ o_i \neq 0 \tag{1}$$

where o_i is the empirically observed change in indicator i and $\hat{o}_{i,j}$ is the change in indicator i of model set-up j. The error is normalised by dividing the indicator's absolute deviation by the indicator's observed absolute value. This allows us to weigh all deviations in indicators equally, irrespective of their absolute scale.

The degree to which a model set-up can replicate the empirically observed changes is subject to the model parametrisation. Key parameters influencing the behaviour of the agricultural system include land supply elasticity ε_n, the substitution elasticities σ for fertiliser and pesticides and the substitution elasticity governing the intensification margin, that is substitution between land and the fertiliser composite. The base model parametrisation for these key elasticities relies on estimates derived from the literature or based on our own assumptions, as reported in Appendix A. These base parameter values are subject to high levels of uncertainty. By calculating the normalised error for each model set-up, we try to calibrate parameter values resulting in the closest possible replication of the empirical estimates. Since we do not know the parameters that result in the lowest normalised error, we apply a stochastic process.

We use a uniform distribution to randomly draw 2000 elasticity values for each of the five model parameters between the lower- and upper-bound ranges reported in Table 3. The random values are generated using the statistical software package R (v.4.0.3; R Core Team, 2020) and the Latin hypercube sampling technique (package lhs; Carnell, 2020), assuming statistical independence between the parameter values. The lower bound of the uniform distribution is 0.1, except for land supply elasticities, for which it is 0.01[2] (Table 3), while the upper bound is 3.6 in the case of the substitution elasticity for chemical and organic fertiliser, which we deem potentially highly substitutable. A lower–upper-bound factor is applied to the remaining parameters since we either assume a lower level of substitutability or have higher confidence in the base elasticity value, as in the case of land supply elasticities estimated for South Asia (Eickhout et al., 2009).

3.4 | Model database

The database used is a 2012 Social Accounting Matrix (SAM) for Bhutan wherein the structure of economic institutions and agents is determined (Feuerbacher et al., 2017). The 2012 SAM was modified by disaggregating the agricultural sector according to conventional and organic activities (Appendix C). Organic activities predominantly represent organic-by-default farming practices, and only a negligible share is certified organic, for which farmers receive a price premium (Feuerbacher et al., 2018). This modified base SAM forms the database for the *benchmark* and represents the basis for the SAM used in the *fieldops* model set-up.

The base SAM consists of 111 accounts. Thirty-nine commodities are produced, and 24 are either outputs or inputs of agricultural production. There are 37 activities, of which 26 are directly related to agriculture. The SAM has 14 factor accounts, of which 10 are needed for agriculture.

[2]In case of CES elasticities in the production structure, a lower bound below 0.1 is associated with technical difficulties of running a large number of stochastic iterations.

The labour market is segmented into three labour types: agricultural, skilled and unskilled labour. Arable land is disaggregated into irrigated land used for paddy production and rainfed land for all remaining crops. There are four livestock-related factor accounts: pasture land, cattle, bulls (for draught power) and other animals. Capital is broadly disaggregated by ownership of enterprises (incorporated capital) or households (informal capital). Informal capital is further disaggregated into power tillers used for cropping activities and other informal capital. Incorporated capital is divided by ownership of private or public enterprises.

There are seven household accounts, which are disaggregated by their main source of income. Agricultural households are classified as such if at least one household member is reported to work in agriculture. In the database, there are two agricultural households subdivided by access to land, that is farm and landless households, and there are five nonagricultural households disaggregated by urban and rural residence and their main source of income (skilled or unskilled labour or, in the case of urban households, other income).

3.5 | Incorporation of field operations into the model database

In the *fieldops* model set-up, we modify the base SAM to incorporate 13 major field operations as presented in Table 1. The compilation process and underlying data are presented in Appendix D, and the corresponding model equations are documented in Appendix E. Each field operation is an activity producing a corresponding field operation (service) commodity that enters the crop-producing activity as a production input.

While the 2012 SAM for Bhutan already contains information on various inputs (e.g. manure and chemical fertiliser), explicit modelling of field operation allows us to include additional information on how much agricultural labour is involved in applying these inputs. For example, organic PP is known to be much more labour-intensive than chemical PP. The technological trade-off can result in significant differences in labour intensity. For example, a recent study interviewing 726 paddy farmers in Bhutan found organic farmers to have 11% greater total labour requirements than conventional farmers due to manual weeding and the application of manure (Tashi & Wangchuk, 2016). Due to data limitations, we assume the same input–output structure for each field operation across cropping activities. For example, each unit of chemical protection involves the same ratio of labour and pesticides independent of cropping activity. However, we use available data on the input levels per crop to derive crop-specific input structures of the various field operations.

4 | MODEL SCENARIOS

Bhutan is among the fastest growing economies in the world, with an annual average real growth rate of 6.9% in GDP per capita (World Bank, 2020). The economic growth is largely fuelled by investments in hydropower and a rapidly growing service sector (World Bank, 2016). The agriculture sector is lagging in terms of annual growth, and in particular, younger generations are leaving rural areas. The share of labour employed in agriculture and forestry has been declining by approximately one percentage point per year (Figure 3). Consequently, labour shortages have become the most urgent constraint reported by farmers (MoAF, 2019a), which has triggered various policy responses, such as the provision of investment subsidies and hiring services for farm machinery (Christensen et al., 2012). Against this background, we simulate two types of scenarios. The *Reference* scenario reflects the structural changes in Bhutan's economy between 2012 and 2018. This scenario is also used to conduct the benchmark analysis between the *benchmark* and *fieldops* model set-ups. Subsequently, three policy scenarios are simulated to inform policy responses to mitigate labour shortages. The policy scenarios are

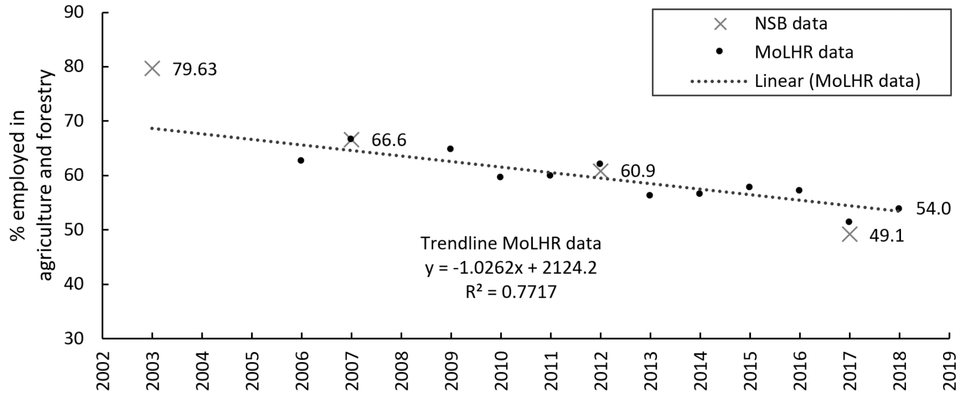

FIGURE 3 Changes in agricultural employment between 2003 and 2018 (*Source*: Own compilation based on data from the Ministry of Labour and Human Resources (MoLHR; 2019) and the National Statistics Bureau of Bhutan (NSB, 2018).

simulated with the *fieldops* model and are assessed against the respective *Reference* scenario outcome.

4.1 | Reference scenario

The exogenous shocks used to simulate the *Reference* scenario are presented in Table 2. We focus on the main macro-level changes (total factor productivity, investment, government expenditure, capital stock and labour force) and yield and price changes for agricultural commodities. Overall, the labour force grew by 6.2% between 2012 and 2018, but employment outside the agricultural sector (skilled and unskilled) increased by 25.0%, while agricultural employment decreased by 5.9%. In total, the share of agricultural employment dropped from 60.9% to 54.0% between 2012 and 2018 (Figure 3).

The drift of workers from agriculture to the secondary and tertiary sectors in this period can be explained by high wage differentials. According to 2012 SAM satellite account data, the (imputed) daily wages of unskilled workers were on average more than five times higher than those of farm workers (Feuerbacher et al., 2017). Given that the availability of agricultural labour declines, we expect a strong increase in agricultural wages as a result of the exogenous shocks on Bhutan's economy. We simulate this labour exodus over six years by reallocating 5.9% of agricultural households' physical agricultural labour endowment to their unskilled labour endowment, that is 5.9% of workers formerly employed in agriculture now find employment in nonagricultural sectors.

4.2 | Policy scenarios

The increasing shortage of agricultural labour has brought up several policy options to mitigate the decline in agricultural production and land use and to maintain a certain degree of food self-sufficiency. Therefore, in a second step, we simulate three policy responses:

1. *Public_Tiller*: Enhancing the use of labour-saving machinery used for land preparation and harvesting by expanding existing state-run power-tiller hiring services.

TABLE 2 % changes (in real terms) in macro-level indicators, world market prices and agricultural yields between 2012 and 2018

Indicators	2012–2018	Annualised
Macro-level indicators[a]		
GDP	34.3	5.0
Total factor productivity[b]	15.2	2.4
Investment	−3.3	0.5
Current account balance	−31.5	−6.1
Government budget	14.3	2.3
Production factors		
Capital returns[c]	21.8	3.3
Skilled labour	25.0	3.8
Unskilled labour	25.0	3.8
Agricultural labour	−5.9	−1.0
Dairy cattle	6.1	1.0
Bulls	−8.3	−1.4
Other animals[d]	37.4	5.4
Commodities		
World market price changes		
Rice	−8.9	−1.5
Maize	−40.4	−8.3
Other cereals	−26.4	−5.0
Vegetables[e]	−3.1	2.9
Potato	−3.1	2.9
Spices	24.5	3.7
Fruits	−1.5	−0.3
Beef	8.0	1.3
Other animal products	7.5	1.2
Dairy products	7.5	1.2
Fertiliser	−6.7	−1.2
Pesticides	16.9	2.6
Production activities		
Yield changes		
Rice	14.8	2.3
Maize	30.4	4.5
Other cereals	−14.8	−2.6
Vegetables	4.5	0.7
Potato	5.0	0.8
Spices	−42.8	−8.9
Fruits	−35.5	−7.0

Source: Authors' own compilation based on NSB, 2020, MoLHR, 2013, 2019, MoAF, 2013a, 2013b, 2019a, 2019b; FAO, 2020b; MoAF, 2022, World Bank, 2022, Ministry of Finance, 2020.

[a] Changes in economic indicators and prices are reported in real terms. Nominal prices were deflated using GDP deflator data for Bhutan (World Bank, 2022).

[b] The change in total factor productivity is set as the average across all model set-ups when estimated as a residual running the Reference scenario with exogenous GDP changes.

[c] Estimated from changes in capital formation assuming a 5% capital return and 16.4% annual depreciation rate.

[d] In 2012, Bhutan was affected by the avian influenza H5N1 (bird flu) explaining the strong increase in other animal population.

[e] Assumed to be equal to price change in potato.

2. *Lib_Agchem*: Supporting the intensification of crop production by removing import tariffs of agrochemical inputs (which are 100% imported).
3. *Foreign_Lab*: Introducing a quota granting work permits for the (temporary) employment of foreign (Indian) workers within Bhutan's agricultural sector.

These policy responses reflect the current debate on which measures the Bhutanese government could undertake (Christensen et al., 2012; Feuerbacher, 2019). In the *Public_Tiller* scenario, we expand the capacity of existing state-run power-tiller hiring services by 150%, which corresponds to an increase in the supply of total power tillers (machinery capital) of 24.6%. To avoid an endowment shock, we reduce the supply of public capital by the same value. In the *Lib_Agchem* scenario, we remove the import tax levied on chemical fertilisers and pesticide imports (the rate was approximately 11% for both in the base). In the *Foreign_Lab* scenario, the number of work permits granted (and thus the absolute increase in foreign workers) is equal to the reduction in agricultural workers in the *Reference* scenario (5.9%). Hence, the number of agricultural workers would remain unchanged, but the labour wages paid to foreign workers present factor income accruing to the rest of the world. Importantly, the scenarios are simulated in addition to the effects of the *Reference* scenario.

4.3 | Model closures

All model set-ups use identical model closures. The consumer price index (CPI) serves as the model's numéraire. We assume that Bhutan is a small country and faces fixed world market prices. The external balance (foreign savings) is fixed and cleared by a flexible exchange rate. The models are investment-driven; the investment quantities are fixed; and the investment savings account is cleared by flexible household saving rates. Government savings are fixed in real terms, and income tax rates vary (additively) to clear the government account.

We impose a medium-term horizon for clearing the factor accounts, which reflects the speed of structural change in Bhutan's economy in the recent past. The supplies of each type of capital are fixed and perfectly mobile across activities. All labour accounts, skilled, unskilled and agricultural labour, are perfectly mobile across activities: They are segmented by skill level, which cannot be altered, that is no labour mobility across skill level. Land is perfectly mobile within its land type across cropping activities. Note that all factors are only mobile between activities that employ the respective factor category in the base SAM. We implement a land supply curve to account for 21% of arable land left fallow in Bhutan (Feuerbacher et al., 2020). Land supplies depend on the land rental rate and approach an asymptote of maximum land supply as the factor price for land goes towards infinity. In the base model parametrisation, we assume an inelastic supply of land with price elasticity $\varepsilon_n = 0.8$ for irrigated and rainfed land following the estimate of Eickhout et al. (2009) for the South Asian region.

5 | RESULTS

5.1 | Model performance in replicating empirical changes

All model set-ups are used to simulate the above-described *Reference* scenario using the 2000 different randomly drawn combinations of elasticity values. Table 3 reports the combination of calibrated elasticity values that result in the least normalised error (i.e. the remaining 1999 model runs are disregarded). Compared with the base elasticity values, the normalised error is reduced by 74% in the case of the *fieldops* model. By contrast, the normalised errors for the

TABLE 3 Range and calibrated elasticity values for main model parameters

		Model set-up		
		Benchmark_ CES	**Benchmark_ Leontief**	**Fieldops**
Land supply elasticity for rainfed land	Base[a]	0.80	0.80	0.80
	Calibrated (0.01–2.4)[b]	1.79	1.77	2.33
Land supply elasticity for irrigated land (paddy land)	Base[a]	0.80	0.80	0.80
	Calibrated (0.01–2.4)[b]	0.37	0.07	0.14
Substitution elasticity for pesticide application <=> manual weeding	Base[a]	NA	NA	1.20
	Calibrated (0.1–3.6)[b]	NA	NA	2.12
Substitution elasticity chemical fertiliser <=> manure	Base[a]	1.20	1.20	1.20
	Calibrated (0.1–3.6)[b]	3.24	3.10	3.44
Substitution elasticity for land <=> aggregate fertiliser	Base[a]	0.40	0.40	0.40
	Calibrated (0.1–1.2)[b]	0.19	0.18	0.91
Average normalised error	With base elasticities	2.96	3.41	2.67
	With calibrated elasticities	2.09	1.31	0.68

[a] Base elasticity values are determined based on available estimates from the literature. See also Appendix A.

[b] Calibrated elasticity values are those that result in the least normalised error when using randomly generated combinations of elasticity parameters. The respective lower- and upper-bound elasticity values are reported within parentheses.

benchmark_CES and *Leontief* set-ups are reduced by 29% and 61%, respectively, and in absolute terms remain much higher than those of the *fieldops* model. We note here that our objective is to calibrate parameter values for the case of Bhutan. The calibration approach itself is transferrable to other empirical cases, but this does not hold for the calibrated parameter values, which are fitted to the Bhutanese context.

Figure 4 shows how each of the model set-ups performs with the base and calibrated elasticity values when compared to the empirically estimated changes in land and agrochemical use. All model versions are consistent with the empirically observed changes in terms of change in signs. Yet, with the exception of changes in paddy cultivation, all set-ups largely underestimate the magnitude of change with base elasticity values. Thereby, the *benchmark_CES* model leads to the highest normalised error (Table 3). With respect to agrochemical use, only the *fieldops* model shows consistent and substantial increases in use. Using the calibrated elasticity values, the results from the *fieldops* model have the least deviations from the observed empirical changes, as also reflected by the normalised error. The *benchmark_Leontief* model is best suited to replicate the changes in rainfed land use, but in contrast to the *fieldops* model, it fails to adequately replicate the changes in agrochemical use. The *benchmark_CES* model still has a poor replication of the empirical changes, except for changes in paddy rice area. Only the *fieldops* model allows replicating the strong observed increase in agrochemical use.

The *fieldops* and *benchmark* models report similar land supply elasticities, that is a highly inelastic price response for irrigated land and a fairly elastic one for rainfed land. The calibration procedure returns substitution elasticities for chemical and organic fertiliser, which point to very high substitutability. This seems implausible if only the commodity input is considered, since the application of organic fertilisers requires substantially more labour input compared with chemical fertilisers (see Table 1). The *fieldops* model considers the substitution of both types of fertilisers including the required labour inputs, making these inputs more comparable and thus more likely to be highly substitutable. This nevertheless remains an area of

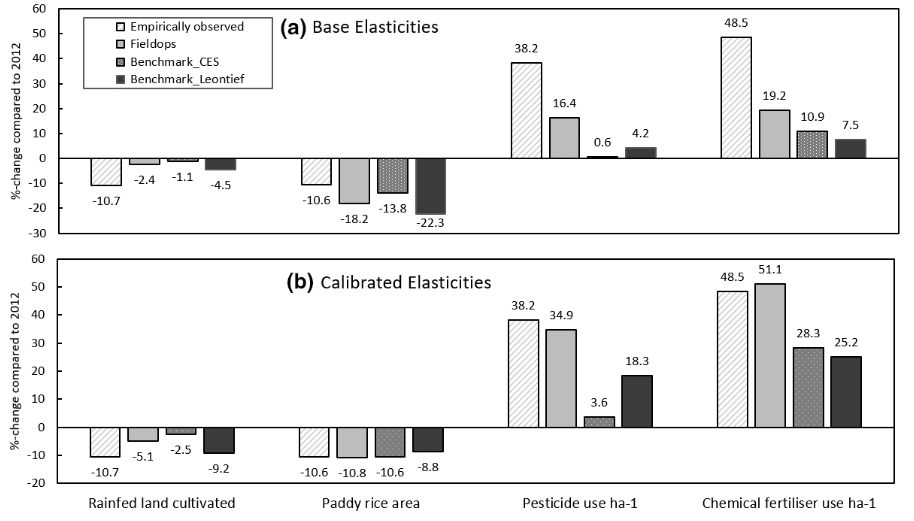

FIGURE 4 Comparison of model results to empirical changes in key indicators observed or estimated from trends occurring between 2012 and 2018 using (a) literature-grounded base elasticities and (b) calibrated elasticities. The empirically observed changes in land use are based on official agricultural statistics (MoAF, 2013b, 2019a). Changes in agrochemical use are estimated by applying a linear trend analysis of 5-year moving averages. The annual quantities of chemical fertiliser use are taken from FAOSTAT (FAO, 2020a), and data on the use of total pesticides are taken from COMTRADE (UN, 2020) and Bhutan Trade Statistics (Ministry of Finance, 2020).

speculation since, according to our knowledge, there are no empirical estimations of substitution elasticities of these two field operations.

In the *fieldops* model, the normalised error is 48% or even 67% lower than in the *benchmark_Leontief* and *benchmark_CES* models. This demonstrates that the *fieldops* model outperforms both benchmark set-ups. Yet, this is only one indicator used to compare the model performance of the different model set-ups. For instance, the *benchmark_Leontief* requires only minimal changes to existing model structures to achieve a reasonably good result. In addition, the plausibility of broader results in the agricultural sector also needs to be assessed, which we do in the following.

5.2 | Comparing agricultural sector results across model set-ups

This section compares the agricultural sector results of the *fieldops* and the two *benchmark* model set-ups using the calibrated elasticity values (see Table 3). At the macro-level, the three set-ups report similar positive effects on Bhutan's economy (Table 4) following the *Reference* scenario, which reflects the structural change between 2012 and 2018 (see Table 2). However, there are substantial differences in how the agricultural sector is affected.

Agricultural wages increase between 35% in the *benchmark_CES* set-up and 46% in the *fieldops* set-up, reflecting different degrees of substitutability of agricultural labour, while returns of cropland decrease (Table 4). In the *benchmark_CES* set-up, fertilised land and labour are substitutable in the value-added nest (Figure 2), which allows to (partially) offset the reduction in the workforce with increasing land supply. Therefore, the *benchmark_CES* model is the least constrained, and its increase in agricultural wages and decrease in cropland rents are the lowest among the three set-ups. From an agronomic perspective, it is difficult to assess to what degree the land-labour substitutions reported by the *benchmark_CES* set-up are plausible, as unlike in the *fieldops* model, it is unknown for which operations labour requirements are reduced.

The *fieldops* and *benchmark_Leontief* set-ups do not allow for a direct substitution between land and labour. This results in a more stable labour intensity compared with the *benchmark_CES* set-up, as shown in the lower part of Table 5 (and in Appendix F for single crops). In the *fieldops* set-up, there is a more pronounced difference between conventional and organic cropping. As conventional cropping allows for more labour-saving field operations, such as chemical fertilisation and PP, the labour intensity of conventional cropping declines stronger. Also, farmers switch to the production of less labour-intensive crops. Due to both effects, conventional cropping expands, while organic crop production declines (Appendix G).

TABLE 4 Macro-level changes relative to the base

GDP components (valued at base prices)		Base share of GDP (%)	Change compared with base (%)		
			Benchmark_CES	Benchmark_Leontief	Fieldops
GDP		100.0	34.4	34.4	34.6
Absorption (C+I+G)		134.2	21.1	21.0	21.1
Consumption (C)		44.6	48.3	48.2	49.5
Agricultural households		16.4	29.3	29.3	30.3
Nonagricultural households		28.2	56.7	56.6	58.2
Investment (I)		71.9	2.6	2.6	2.2
Government (G)		17.8	26.0	26.0	25.5
Exports (E)		36.2	72.2	71.7	71.1
Imports (M)		70.4	28.0	27.7	27.3
Trade balance (E-M)		−34.2	−18.8	−18.9	−19.1
Other macro-level indicators					
Exchange rate (*Domestic currency/ foreign currency*)			−2.1	−2.0	−1.7
Average household welfare[a]			37.8	37.6	38.7
Agricultural households			27.5	27.4	28.4
Nonagricultural households			42.3	42.2	43.3
Factor prices					
		Base (USD per month)			
Labour	Agricultural	49.7	35.0	39.2	45.9
	Unskilled	263.0	−0.9	−0.9	−0.6
	Skilled	395.5	5.4	5.5	6.1
Land	Paddy		−23.7	−66.2	−47.7
	Rainfed		−5.3	−8.3	−5.2
	Pasture land		25.1	26.6	−16.3
Capital	Power tillers		0.0	10.8	1.3
	Cattle		5.8	4.0	−22.8
	Bulls		43.9	58.7	−25.3
	Other animals		19.0	20.2	−24.6
	Unincorporated		6.7	6.7	7.2
	Public		18.4	18.3	18.7
	Informal		−0.8	−1.3	−0.7

[a] Measured as the equivalent variation as a share of base income.

TABLE 5 Land use and input intensity

Land use

			Change compared with base (%)		
Land type		**Base (hectare)**	**Benchmark_CES**	**Benchmark_Leontief**	**Fieldops**
Total cropped land	TOTAL	76,017	−4.3	−9.1	−6.3
	Irrigated	16,873	−10.6	−8.8	−10.8
	Rain-fed	59,144	−2.5	−9.2	−5.1
Conventional	TOTAL	14,107	−3.8	−5.5	−6.7
	Irrigated	4,368	−5.8	1.8	−4.9
	Rain-fed	9,738	−3.0	−8.8	−7.5
Organic	TOTAL	61,911	−4.4	−9.9	−6.2
	Irrigated	12,505	−12.2	−12.5	−12.8
	Rain-fed	49,406	−2.4	−9.3	−4.6
Fallow land		21,291	15.3	32.6	22.6

Input intensity

			Change compared with base (%)		
Land type	**Input**	**Base-quantity**	**Benchmark_CES**	**Benchmark_Leontief**	**Fieldops**
Total cropped land	Labour	10.0 days/100 USD output	−6.3	−2.6	−1.5
	Total nutrients	104.4 kg NPK/ha	−2.6	−4.6	5.3
	Manure	91.9 kg NPK/ha	−7.1	−8.7	−1.2
	Chemical fertilizer	12.5 kg NPK/ha	30.8	25.1	53.3
	Pesticides	–[a]	5.6	18.2	37.0
Conventional	Labour	8.7 days/100 USD output	−11.1	−4.7	−7.4
	Chemical fertilizer	67.6 kg NPK/ha	30.2	20.3	53.9
	Pesticides	–[a]	5.1	13.8	37.5
Organic	Labour	10.4 days/100 USD output	−4.3	−1.2	0.8

[a]The composition of pesticides is unknown but assumed to remain unchanged.

Overall, more land is left fallow with all set-ups (upper part of Table 5). The acreage under organic farming is especially reduced due to its comparably high labour intensity (lower part of Table 5, Appendix C) and given that there is no price premium for organic produce in Bhutan, while conventional farming even expands somewhat. The decline in land use is highest for irrigated (paddy) land due to the high labour intensity of paddy production, causing farmers to switch to less labour-intensive crops.

Despite the overall reduction in cropped acreage and increasing availability of power tillers as part of the structural change simulated, the price of power tillers does not decline (Table 4). In the *benchmark_CES* set-up, the CES elasticity at the aggregate value-added nest allows for a reaction to the more expansive capital–labour aggregate by substituting it with land (Figure 2). In other words, similar to labour, power tillers could be replaced to some extent by the expansion of agricultural areas, which balances out the substitution effect at the labour–capital nest. In the *benchmark_Leontief* set-up, this is not possible, which is why here the substitution between labour and power tillers dominates, resulting in increasing rental prices of tillers. In the *fieldops* set-up, a direct substitution between tillers/labour and land is not possible by the design of the production structure. Instead, the existence of more labour-efficient ploughing techniques is acknowledged by the different land preparation operations, which can be substituted for one another (Figure 2). Despite the reduction in land use, this results in a higher demand for mechanical ploughing and thus a moderate increase in tiller prices. In contrast, labour-intensive manual ploughing is especially reduced (−69.0%), while draught bull ploughing remains constant (Figure 5). The extent to which demand for field operations and their prices change is a useful information to identify where agricultural technology interventions (e.g. mechanising harvesting; reducing labour needs for crop guarding) may be most worthwhile.

A crucial difference between the model set-ups is that the *fieldops* set-up captures the technological development away from animal-based manure and draught power towards their modern counterparts, chemical fertiliser and mechanised ploughing. The lower demand for manure and draught power reduces their producer prices to such an extent that factor rents specific to livestock fall strongly (Table 4). These relationships are not captured in the

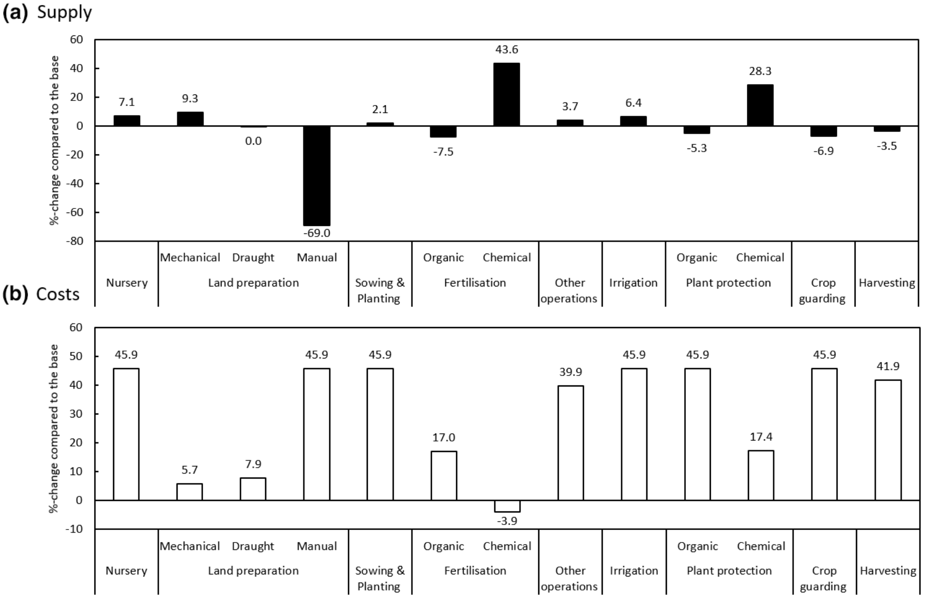

FIGURE 5 Supply (use) and price (cost) changes for field operations.

benchmark set-ups where manure and draught power demand increases as there is no link to the actual labour required to use these inputs in cropping.

Furthermore, the *fieldops* set-up allows for a more detailed analysis of input use in the cropping sector. For most field operations, labour is the main input. Thus, the associated costs increase at similar rates as the wages of agricultural workers (Figure 5). Chemical fertilisation and PP depend to a larger extent on nonlabour inputs, namely imported chemical fertilisers and pesticides. For these, the world market price drops by 6.7% and increases by 16.9%. Since they become relatively cheaper compared with agricultural wages, more farmers are incentivised to use chemical inputs, that is a switch from organic to conventional cropping activities. In the *fieldops* set-up, this switch can be observed by the use of organic versus chemical fertilisers and PP. As shown in the lower section of Table 5, this change in input intensity is much less pronounced in the *benchmark* set-ups. On aggregate, with the two *benchmark* set-ups, the total nutrient supply is decreasing, possibly resulting in soil mining, while it increases with the *fieldops* set-up, pointing at intensification.

5.3 | Analysis of policies mitigating agricultural labour shortages

In this section, the *fieldops* approach (with calibrated model parameters) is applied to analyse the effectiveness of different policy measures in mitigating the adverse effects of labour shortages in the agricultural sector caused by the *Reference* scenario. The results are summarised in Table 6. The first column presents the effects of the *Reference* scenario without any policy response and the following columns report the outcomes of three policy scenarios as deviations from the *Reference* scenario.

The ambitious increase in the supply of public power tillers (Scenario *Public_Tiller*) has a very limited effect on macroeconomic indicators. In alignment with expectations, the higher availability of power tillers leads to an expansion of crop production and thus land use since the price of ploughing (power tillers and bulls) and animal manure declines. As prices of chemical inputs remain constant, organic production expands relatively more. Overall, agricultural production increases by 0.6% compared with the *Reference* scenario. This policy results in an increase in food self-sufficiency, especially for rice. Yet, it is by far not enough to offset the initial reduction caused by the *Reference* scenario. An interesting aspect here is that farmers in Bhutan predominantly refrain from slaughtering animals because of their Buddhist or Hindi beliefs (Samdup et al., 2010). Hence, the ‘phasing out’ of using bulls for ploughing would require much more time, while less utilised bulls still require care and feed.

The removal of import taxes on chemical fertilisers and pesticides (Scenario: *Lib_AgChem*) reduces their purchasing prices by 9.4% and 9.3% respectively. This only benefits the conventional crop production sector, where cultivated land increases by 0.7%. With largely unaffected organic production, this leads to a negligible increase in agricultural production and self-sufficiency. The labour intensity declines in alignment with much higher levels of agrochemical use per hectare, but there is still a slight increase in land use of 0.1%. Manure prices fall, reflecting the substitution of labour-intensive manure with chemical fertiliser in conventional cropping. The overall low magnitude of this shock with respect to macroeconomic indicators is due to the low intensity of agrochemical usage in Bhutan. The results show that even for only a slight increase in farm household welfare (0.3%), chemical application rates need to increase considerably (Table 6). The potentially adverse environmental impacts of such a policy are unknown and not reflected in this study. They might be negligible, given the low intensity of agrochemical use in Bhutan. However, for instance, Butachlor, a herbicide widely used by paddy farmers in Bhutan, is known to result in widespread negative impacts on amphibians (Liu et al., 2011).

TABLE 6 Main results of policy scenarios (% changes)

			Reference scenario	Public_ Tiller	Lib_ AgChem	Foreign_ Lab
			Compared with base	Compared with reference scenario		
Macro-level indicators						
GDP			34.6	0.0	0.0	0.4
Private consumption			49.5	0.0	0.0	0.6
Trade balance			−19.1	0.0	0.0	−1.4
Exchange rate (domestic per foreign currency units)			−1.7	0.1	0.0	0.2
Welfare	Urban households[a]	Skilled labour	43.0	0.2	0.1	2.5
		Unskilled labour	38.9	0.3	0.1	2.8
		Other income	63.0	0.4	0.1	3.7
	Rural households[a]	Skilled labour	35.2	0.2	0.1	2.6
		Unskilled labour	36.6	0.3	0.1	3.1
		Farm	27.9	0.2	0.3	−1.0
		Landless	35.9	0.6	0.1	−3.1
Income	Urban households[a]	Skilled labour	35.4	0.1	0.0	0.6
		Unskilled labour	28.8	0.1	0.0	0.5
		Other income	68.3	0.2	0.0	1.4
	Rural households[a]	Skilled labour	30.1	0.1	0.0	0.5
		Unskilled labour	29.8	0.1	0.0	0.6
		Farm	28.0	0.0	0.1	−0.4
		Landless	37.6	0.2	0.0	−0.9
Wages	Agricultural		45.9	0.4	0.0	−5.3
	Unskilled		−0.6	0.0	0.0	0.3
	Skilled		6.1	0.1	0.0	0.3
Producer prices	Agriculture		15.4	−0.9	−0.2	0.0
	Food processing		2.4	−0.1	0.0	−0.9
	Rice		3.9	−0.7	−0.1	−0.9
	Manufacturing		−2.7	0.1	0.0	0.4
	Other industries		−3.0	0.1	0.0	0.4
	Services		−4.6	0.1	0.0	0.3
Domestic production	Total		37.6	0.0	0.0	0.5
	Agriculture		3.3	0.6	0.2	2.3
	Food processing		18.1	0.6	0.1	4.7
	Rice		2.3	1.8	0.4	3.2
	Manufacturing		78.9	−0.2	0.0	0.3
	Other industries		19.1	−0.1	0.0	−0.2
	Services		49.1	0.0	0.0	0.3

(Continues)

TABLE 6 (Continued)

			Reference scenario	Public_ Tiller	Lib_ AgChem	Foreign_ Lab
			Compared with base	Compared with reference scenario		
Agricultural sector indicators						
Self-sufficiency		**Base rate**				
	Food	67.4	−11.4	0.4	0.1	2.1
	Cereals	62.9	−22.2	1.2	0.3	0.8
	Rice	56.5	−13.8	1.6	0.3	2.8
Input prices/ rents	Cropland		−10.2	0.8	0.1	2.7
	Tiller		1.3	−18.4	0.2	3.9
	Bulls		−25.3	−28.0	0.2	26.1
	Manure		−15.1	−2.0	−1.3	4.6
	Chemical fertiliser		−8.2	0.1	−9.4	0.4
	Pesticide		13.8	0.1	−9.3	0.4
Input use	Land	Total	−6.3	1.2	0.1	4.2
		Conventional	−6.7	1.0	0.7	2.7
		Organic	−6.2	1.3	−0.02	4.6
	Labour (per value of output)		−1.5	−0.9	−0.4	1.6
	Total nutrients (per ha)		5.3	−0.6	1.8	0.2
	Manure (per ha)		−1.2	−0.4	−1.5	1.0
	Chemical fertiliser (per ha)		53.3	−1.4	17.2	−3.4
	Pesticides (per ha)		37.0	0.0	7.7	−6.0

[a] Representative household groups are disaggregated by location and their main source of income. See Feuerbacher et al. (2017) for more details.

Both the *Public_Tiller* and *Lib_AgChem* scenarios come at a cost to the government's budget. Increasing the provision of power tillers requires the government to reduce investments in other sectors. Liberalising agrochemical imports reduces tariff revenues, which is offset by negligible endogenous changes in the direct income tax. By contrast, introducing a quota for the employment of foreign workers (Scenario *Foreign_Lab*) only entails administrative costs, which are arguably low but not reflected in the model. The *Foreign_Lab* policy would have the greatest potential to mitigate labour shortages. Unlike the other two options, this scenario has some pronounced macroeconomic effects. It increases GDP by 0.4% and private consumption by 0.6%, while agricultural and total production rise by 2.3% and 0.5% respectively. Agricultural wages fall substantially by 5.3%, yet skilled and unskilled wages slightly increase, mostly to the benefit of nonagricultural households. Despite the drop in agricultural wages, producer prices of agricultural remain constant since the increase in land use (+4.2%) is accompanied by increasing land prices (+2.7%). Food self-sufficiency increases (+2.1%), although the reduction experienced due to the *Reference* scenario is not reverted. The higher availability of labour predominantly benefits organic production (+4.6%). Land cultivated under conventional agriculture increases by 2.7%, while the use of chemical fertilisers and pesticides per hectare drops by 3.4% and 6.0% respectively. Not surprisingly, the decline in agricultural wages leads to a decline in the welfare of agricultural and especially landless households, which is minor compared with their original gains from the *Reference* scenario. By contrast, the welfare of all nonagricultural household groups rises.

6 | DISCUSSION

6.1 | Modelling labour-saving technologies by incorporating field operations

Comparing economy-wide model results to real-world observations (or 'baseline forecasting') is an element of model validation (Dixon & Rimmer, 2013). It may offer guidance on how good deductive methods such as simulation modelling approaches depict trends observed in reality (Sargent, 2013). The calibration approach applied in this study may be a valuable alternative as often no data are available to estimate adequate functional forms and their underlying parameters econometrically. Yet, a disclaimer is warranted that the calibrated parameters are not transferrable to other contexts, as they were fitted to the Bhutanese context. Full-scale model validation is a nontrivial undertaking. The manifold factors affecting an economy are neither known nor observed in their entirety, and if measured, they are prone to measurement error and biases. As done in this study, comparative-static model simulations are mostly conducted in a *ceteris paribus* fashion, that is, only exogenous parameters of interest are changed, while others remain constant. These words of caution should be heeded, but they apply to all three model set-ups equally and may inspire further research in this field of model validation.

We show that common model approaches (which we label *benchmark* set-ups) fail to adequately reflect the labour-saving potential of modern agricultural technologies and, most notably, the use of agrochemicals, while the *fieldops* approach allows for more targeted agricultural scenarios. By incorporating field operations into the agricultural production structure, we can explicitly model technological means to substitute labour with the adoption of machinery, pesticides or chemical fertiliser. Importantly, we separate these substitution relationships since the adoption of a single technology (e.g. applying herbicides) has only limited labour-saving potential.

Generally, the comparison of the *fieldops* model to the two *benchmark* set-ups scrutinises the plausibility of model results and, more specifically, factor substitutions. Modelling land as an imperfect substitute for capital, as in the *benchmark_CES* set-up, is very likely to overestimate the agricultural sector's capacity to compensate for the reduction in labour availability, which is corroborated by the weak replication of the empirically observed changes in agrochemical and land use. Further, the fact that the application of additional fertiliser and chemicals also requires labour is not (explicitly) recognised in the *benchmark* set-ups, where fertiliser represents a substitute for land and pesticide use is bound to the production level (Figure 2) (Note that total aggregate labour use is identical across all model set-ups.).

Including field operations makes substitution relationships much more explicit, allowing us to determine substitution elasticities for labour versus other inputs for each specific task rather than having only one form of land-labour elasticity, representing the aggregated substitution possibilities of the growing season. With the *benchmark* set-ups, it would be difficult to ex ante determine a single substitution elasticity that correctly captures all specific substitution relationships.

While this study demonstrates the possibility of capturing a high level of technical detail using a CGE model, it does not per se imply that the *fieldops* approach is a silver bullet for modelling (smallholder) agriculture, as it requires substantially more data. In case of limited data availability in the context of smallholder agriculture and less focus on agricultural sectoral details, a set-up with a fixed shares relationship between land and labour such as the *benchmark_Leontief* model may be considered the next best alternative, as it avoids unrealistic substitution possibilities. In fact, running the policy scenarios analysed here with the *benchmark_Leontief* model yields similar outcomes for macroeconomic indicators, yet quite substantial differences remain in the agricultural sector (Appendix H). However, according to our review of the literature, the vast majority of studies rely on a CES labour–land substitution relationship. Preparing the literature review for this study, we examined 30 CGE model studies, out of which only Argüello and Valderrama-Gonzalez (2015) used a Leontief nest between land and labour.

6.2 | Further model development options

The incorporation of field operations within the production structure of a CGE model is a contribution towards improving the depiction of agricultural production systems in economy-wide simulation models. The approach requires the necessary data (see Appendix D) to estimate the cost structure of field operations. This investment is particularly worthwhile in countries with a labour-intensive agricultural sector, which holds for most low-income countries in the world.

With better data, technological trade-offs could be modelled at the crop and operation level. While the cost structure of many field operations is similar across crops (e.g. application of manure or crop protection), the mechanisation potential is crop specific and allows for labour savings in most field operations. This applies particularly to harvesting, which compared to all other field operations in Bhutan, requires most labour-days (Table 1). Yet, so far, agricultural machinery is predominantly used for land preparation in Bhutan. Therefore, in this application, land preparation is the only field operation, which allows for mechanisation. However, the field operations model is flexible to integrate more and other technologies (such as different harvesting technologies), depending on their relevance to the specific country context and the availability of an appropriate database.

Field operations are performed in different periods of the cropping season, which naturally calls to also consider the seasonality of labour since labour shortages mainly occur in specific seasons such as during the planting or harvest time. Seasonal labour has been already captured in CGE models (Feuerbacher et al., 2020). In this way, seasonal foreign employment could be integrated as well. However, this would require a considerably more complex production structure. Along the same lines, labour accounts could be disaggregated by gender, which would allow us to focus on the welfare implications of gender disparities in agriculture and other sectors. These additions may be addressed in future research. The incorporation of seasons and field operations could provide the basis to model sequential decision-making in agriculture (Antle, 1983). Yet, this would require switching to recursive dynamic mode and ideally splitting the model into intra-annual periods (see, e.g. Dixon & Rimmer, 2021).

6.3 | Policy implications for mitigating labour shortages in agriculture

As in many other low-income countries, Bhutan's agricultural sector suffers from labour shortages (e.g. Leonardo et al., 2015). However, as this study shows, the potential to promote labour-saving technologies is limited. Bhutan's topography and small-scale subsistence-focussed agricultural sector do not permit the use of large machinery, and even the use of single-axle power tillers in fields may be problematic in some areas. The policy of expanding public power rental services by 150% can be considered ambitious, while its potential to mitigate labour shortages remains limited. The same holds for the liberalisation of agrochemical imports, although this scenario results in considerably increased production intensity. Fostering the use of agrochemicals would be a quite controversial policy in Bhutan, which has ambitions to become the first country with a 100% organic agricultural sector (Feuerbacher et al., 2018).

Only the influx of foreign agricultural labour shows considerable effects to mitigate the labour shortage in agriculture and the associated decline in agricultural production. The simulated quota of allowing 5.9% of Bhutan's agricultural labour force in 2012 to work in agriculture is equivalent to approximately 12,000 workers. Despite the associated transaction cost, this scenario is realistic given the high wage differential between Bhutan and India. As farming in Bhutan is still predominantly semisubsistence focussed with small average landholdings, the scope of worker hiring is primarily limited to commercial farmers with above-average farm sizes. However, allowing Indians to work in agriculture is subject to controversy (Christensen et al., 2012), as farming and rural traditions are perceived to be an integral part of Bhutan's culture. This could possibly be addressed by imposing restrictions, for example by limiting work permits to temporal employment or to Southern regions close to the Indian border.

7 | CONCLUSIONS

This study shows that the selection of an adequate production structure is not trivial for economy-wide analyses of agricultural policies in countries where the agricultural sector is still dominated by labour-intensive smallholder farming systems. We propose a model set-up that explicitly incorporates field operations (e.g. land preparation, weeding or harvesting) into the production structure and thus depicts technological trade-offs such as the use of labour-saving technologies and labour-intensive practices. We conduct a detailed benchmark analysis of the proposed novel model structure by comparing it to observed empirical evidence such that differences can be rigorously traced. The field operations approach allows us to replicate empirically observed changes in agrochemical and land use, while the common approaches found in the literature fail to do so. It avoids opaque and unrealistic adjustment patterns when modelling scenarios of structural change, making behavioural adjustments in the agricultural system more explicit and hence traceable.

We use the field operations model to investigate three policy options to mitigate labour shortages in the agricultural sector of Bhutan. We find that permitting the employment of Indian workers in agriculture has the highest short-term potential in this respect. Subsidising agricultural machinery hiring services and removing import tariffs on agrochemical inputs are found to be less effective.

Modelling field operations and thus the potential of labour-saving technologies adequately in an economy-wide model is of high relevance to researchers and policymakers concerned with agricultural and rural development. Many interventions, such as conservation agriculture, climate-smart agriculture or sustainable intensification, imply higher labour requirements, and their success is often impeded by labour shortages. On the contrary, new technologies such as machinery-sharing platforms, improved crop varieties and agricultural extension services may boost the adoption of labour-saving technologies. These new technologies and practices are being scaled up and disseminated, while processes of structural change and policy reform are taking place. The very nature of economy-wide models allows us to capture these processes and economic linkages beyond the agricultural sector. With the contribution of this article, such models may also be improved to better represent the agricultural sector and the specific realities of labour-intensive, smallholder farming systems.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Arndt Feuerbacher https://orcid.org/0000-0003-3414-5120
Jonas Luckmann https://orcid.org/0000-0003-3657-3778

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Additional supporting information can be found online in the Supporting Information section at the end of this article.

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