INITIATIVE ON Mixed Farming Systems

CGIAR

Mapping mechanization suitability using machine learning, presence data and spatial co-variates:

Methodological approach

Subash Adhikari[1], Pankaj Koirala[1], Sagar Kafle[1], and Powell Mponela[1]

Author affiliation [1]International Maize and Wheat Improvement Center

Published by: International Maize and Wheat Improvement Center
January 2025

The Mixed Farming Systems Initiative aims to provide equitable, transformative pathways for improved livelihoods of actors in mixed farming systems through sustainable intensification within target agroecologies and socio-economic settings.

Through action research and development partnerships, the Initiative improves smallholder farmers' resilience to weather-induced shocks, provide a more stable income and significant benefits in welfare, and enhance social justice and inclusion for 13 million people by 2030.

Activities are implemented in six focus countries globally representing diverse mixed farming systems as follows: Ghana (cereal–root crop mixed), Ethiopia (highland mixed), Malawi: (maize mixed), Bangladesh (rice mixed), Nepal (highland mixed), and Lao People's Democratic Republic (upland intensive mixed/ highland extensive mixed).

Contents

Abbreviations and acronyms

ABC	Alliance of Bioversity International and the International Center for Tropical Agriculture (CIAT)
CGIAR	Consultative Group on International Agricultural Research
CIMMYT	International Maize and Wheat Improvement Center
CSISA	Cereal System Initiative for South Asia
FAO	Food and Agriculture Organization of the United Nations
ha	Hectare
hp	Horsepower
ICARDA	International Center for Agricultural Research in the Dry Areas
IITA	International Institute of Tropical Agriculture
ILRI	International Livestock Research Institute
IRRI	International Rice Research Institute
IWMI	International Water Management Institute
m	Metre
pH	Potential of Hydrogen
SDG	Sustainable Development Goals
MFS	Mixed Farming Systems Initiative

1 MECHANIZATION: HISTORY, STATUS AND MAPPING

Agricultural mechanization has been pivotal in increasing agricultural production efficiency, but in Nepal, the pace of mechanization is slow with subtle tractor usage in Terai (lowland) regions after 1990s (Paudel et al., 2019), which is driven primarily by outmigration and raising labor wages (Takeshima and Justice, 2020). In recent decades, the availability of smaller tilling machinery, particularly mini tillers suitable for hilly regions has enabled the expansion of machinery usage to hilly regions (Prasad, 2020). The expansion has been supported through subsidies by the Government of Nepal amidst several gaps in utilization of the machinery and its service provision (Brown et al., 2021). Despite these efforts and advancements, there exists substantial gaps remain in the machinery utilization and its services in Nepal, limiting impact of these programs (Devkota et al., 2020). One of the notable lack to promote mechaniuzation is Nepal's sloped areas. The hilly areas and terrains are ofter considered to complicate mechanization efforts compared to Terai (flat) areas, highlighting the needs to explore the relatively modern and advance tools to guide policy makers in identifying suitable areas for mechanization promotion. In this context, "Mechanization suitability mapping" can help support if accounted together with several factors including land use, ecological fragility, accessibility, socioeconomics have been used to define mechanization suitability (Yang et al., 2023a). Globally, agricultural mechanization began with the introduction of the steam engine in the 1840s, followed by the advent of internal combustion engines in the 1890s. By the 1920s, highly efficient tractors for plowing were developed, leading to the era of mass tractor farming. It is believed that the widespread adoption of tractors was driven by food and labor shortages (both manual and animal) in agriculture during the Worldthe World War (Karasev, 2023).

In the context of Nepal, agricultural mechanization increased significantly after 1990s. The year 2006 has been pivotal with widespread tractor in Terai, introduction of power tillers and mini tillers in the Hills, and increased adoption of motorized pumps in the Terai (Takeshima and Justice, 2020).

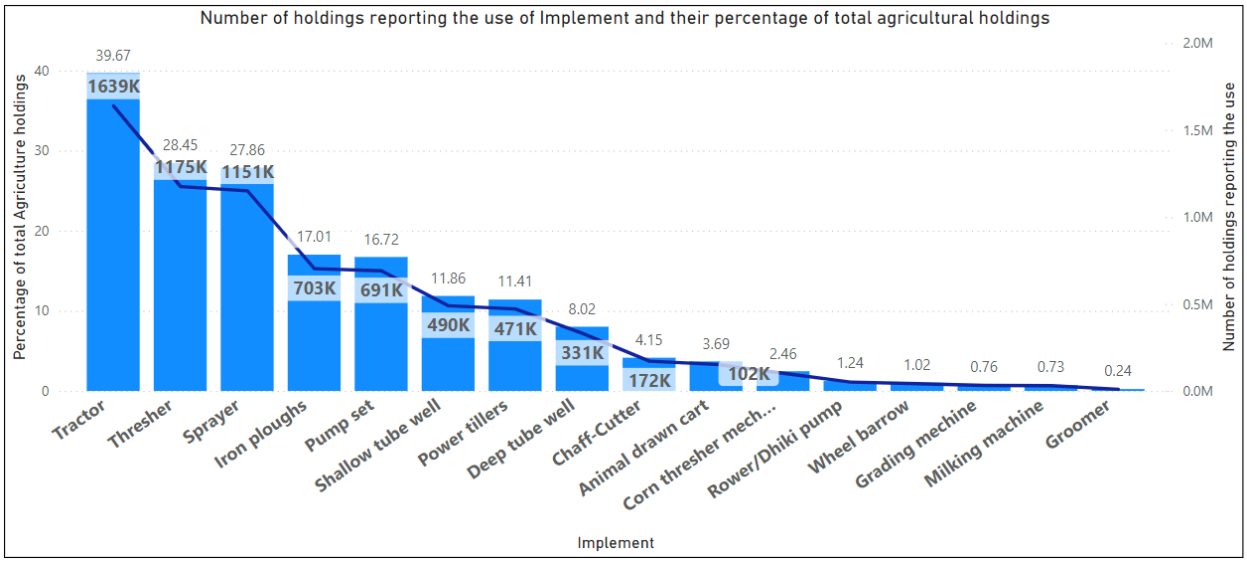

Figure 1: Number of holding reporting the use of implement and their percentage out of total 41,30,789 agriculture household. Source: National Agriculture Sample Census 2021-22.

As of the fiscal year 2021/2022, a significant number of holdings reported using agricultural implements (National Statistics Office, 2023). The national agriculture survey reported 16 major types of machinery or implements being used by Nepalese farmers. Out of a total of 4,130,789 agricultural households, the survey estimated that 39.67% use tractors, 28.44% use threshers, 11.4% use power tillers, while only 2.4% use the groomers (Figure 1). A total of 51.07% of agricultural households use machinery for tillage while the remaining 49.03% could still rely on non-mechanical methods, such as oxen or manual labor. According to the report, 17.01% (702798) of agricultural households use iron ploughs, relying on oxen power for tillage.

Agricultural mechanization in Nepal, which was concentrated in the Terai regions, is gradually increasing in hilly regions, particularly in Bagmati and Gandaki Provinces (Figure 2). In the Terai, all districts report that more than 50% of the agricultural households use tillage machinery. In contrast, only six districts in the hills and mountains report more than 50% of tillage machinery users: Palpa, Kaski, Nuwakot, Bhaktapur, Kavre and Makawanpur. All districts in the mountain and hill regions of Gandaki, Lumbini and Bagmati have more than 10% of agricultural households using tillage machinery, except for Manang, Rukum east and Rolpa. However, most districts in the mountain and hill regions of Sudurpaschim, Karnali and Koshi provinces report very low usage rates (less than 10%). Dadeldhura is the only district in the hills of Sudurpaschim Province with a tillage machinery usage rate exceeding 10%, where 16.25% (low level) of households use tillage machinery. Similarly, Surkhet is the sole district in Karnali Province with usage rate exceeding 10%, where 34.20% of households use tillage machinery. Additionally, except for three mid-hill districts bordering the Terai in Koshi Province all others hilly and mountain districts has usage rate less than 10% of total agricultural households.

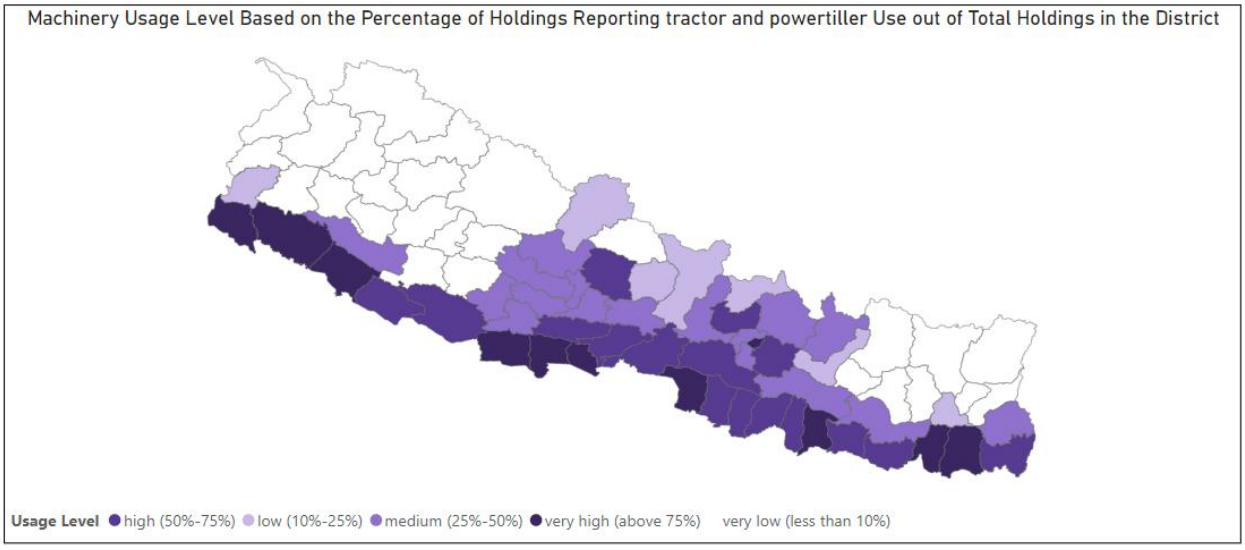

Figure 2: Machinery usage level of different districts of Nepal based on percentage of holding reporting the use of tractor and power tiller out of total holdings in the district. Source National Sample Agricultural Census 2021/22

In an ideal world, all farmers would be assembling and sharing data on usage of mechanization which could give a full state of mechanization. However, in data sparse regions, information is lacking to guide decisions. Practitioners tend to use individual factors such as slope (Grečenko, 1984a). Other studies use expert evaluations to develop mechanization suitability

ratings based on indicator ratings (Amongo et al., 2023a). Other indirect measures include estimating mechanization potential and feasibility for cropping systems using a sample of farms with data on mechanization, crops, and cost of land preparation (Singh, 2006). In Tieling City of Liaoning province in northeastern China, Yang et al (2023a) used random forest based on variates: land use (land cover, vegetation index, land productivity), topography (elevation and slope), soil (pH, organic carbon and micro-organisms), accessibility (roads, servicing centers) farm features (connectivity, aggregation and shape) and socioeconomics (GDP, labour and income) to map land mechanization suitability to support land consolidation program.

This study develops an approach for identifying and mapping suitable areas for promoting mechanization, guides optimal resource allocation decisions within variable landscapes and identifying areas where mechanization would be most profitable. Mechanization suitability mapping is instrumental in supporting the promotion of mechanization by enabling targeted interventions. One notable example is its application in land consolidation programs, as demonstrated by Gürgenç Irmakli & Aydin, 2022). This highlights how such mapping aligns with government initiatives, including Nepal's Mechanization Promotion Policy which envisions land consolidation as a key strategy under its objective 10.1.16 to promote mechanization (Ministry of Agriculture and Livestock Development, 2014).

THE METHODOLOGY

1.1 Study Area

The study area includes the CSISA working districts (Kanchanpur, Kailali, Bardiya, Banke, Dang, Kapilvastu, Rupandehi, Nawalparasi and Surkhet) from where the presence data was collected. Kanchanpur, Bardiya, Banke, Kapilvastu and Rupandehi share a large proportion of flatlands with very few hills terrain. Although conventionally considered as terai districts, Kailali, Dang and Nawalparasi constitute a significant proportion of hilly areas as well. Surkhet represented as a hill district having mostly terraced lands but with relatively flat areas near Bheri river basin. We assume that the difference in topography across districts is the basis for differences in machinery suitability to a large extent.

The database of machinery also included seed drills presence data from some eastern districts collected from the survey of custom hiring center in terai districts.

1.2 Modeling approaches

1.2.1 Maximum Entropy Model

In absence of georeferenced machine usage field data (National Statistics Office, 2023), the study assumes that owners of the machines are located near farms where they are used. Hence, the areas with machines are more likely to be suitable for mechanization. The study builds an approach for mapping mechanization suitability using maximum entropy model (Berger et al., 1996). The Maxent model uses machine learning to predict the probability of finding the equipment in a given space. It classifies land parcels for different machinery usage based on georeferenced machinery presence and various factors that influence the effectiveness and efficiency of agricultural machinery (Figure 3). Originally made for language modelling (Berger et al., 1996), it has been widely

used in large language and classification models to detect physical shapes (Jeon et al., 2003; Mohanty et al., 2013), ecology (Phillips et al., 2006), macroecological suitability patterns (FAO and University of Bonn, 2021) and more recently to map land suitability for farming systems (Kamau et al., 2023).

Using a Bayesian perspective, the principle of maximum entropy states that, given known constraints such as slope, the probability distribution that best represents the data is the one with the greatest entropy, that is the one that best reproduces the data. We apply this to presence only data for the machinery, the probability distribution encompasses all pixels in the study area, the pixels representing the distribution of machinery occurrences in sample points, and the spatial features that are explanatory variables.

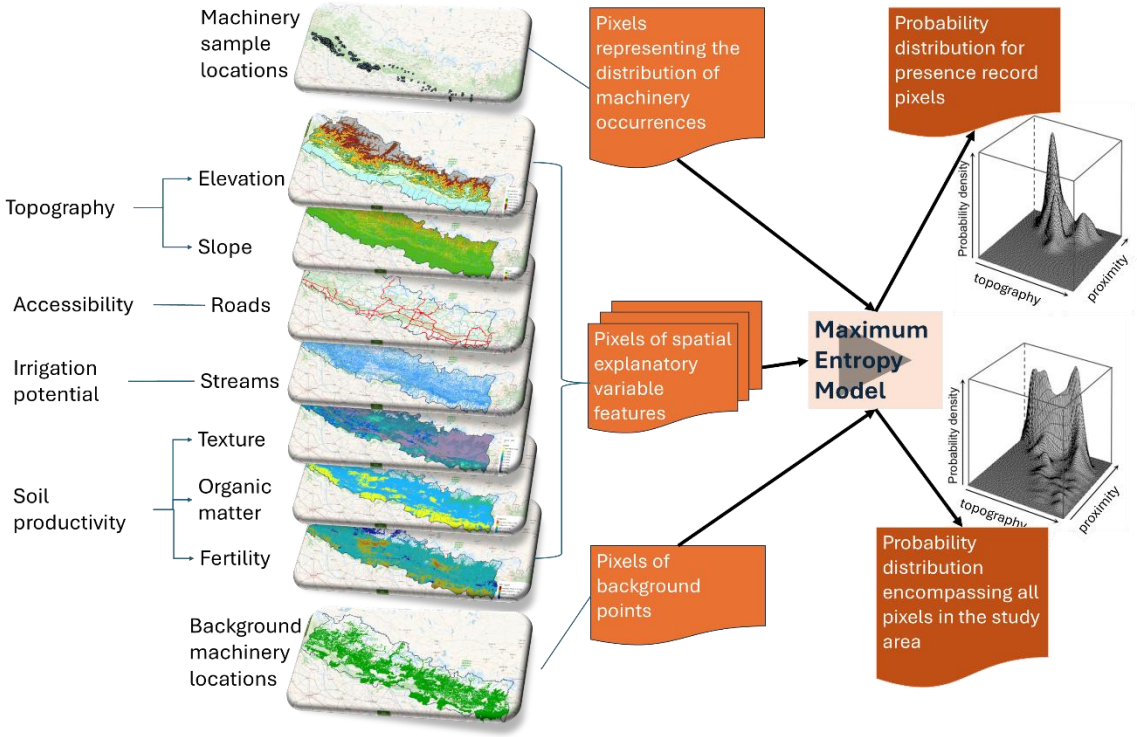

Figure 3: Schematic workflow for mapping mechanization suitability using presence data and spatial covariates.

1.2.2 Presence records

The presence data were collected from CSISA Project which operated between 2009 to 2024 in Nepal. A total of 3,809 machinery owners' data were available for analysis. The dataset includes information on the type of machinery owned, geo locations of the machinery, market distance from the home, ownership type, average annual area of coverage of the machinery. The majority, 3,218 own reaper attachment, 1,477 own two-wheeled tractor (commonly called power tillers), 364 own four-wheeled tractor, 121 own mini tillers and 188 own water pumps. The majority data come from western terai districts, ranging from Kanchanpur to Nawalparasi, while there are fewer datasets from eastern regions, spanning from Nawalparasi to Jhapa. Few data from Surkhet are also included.

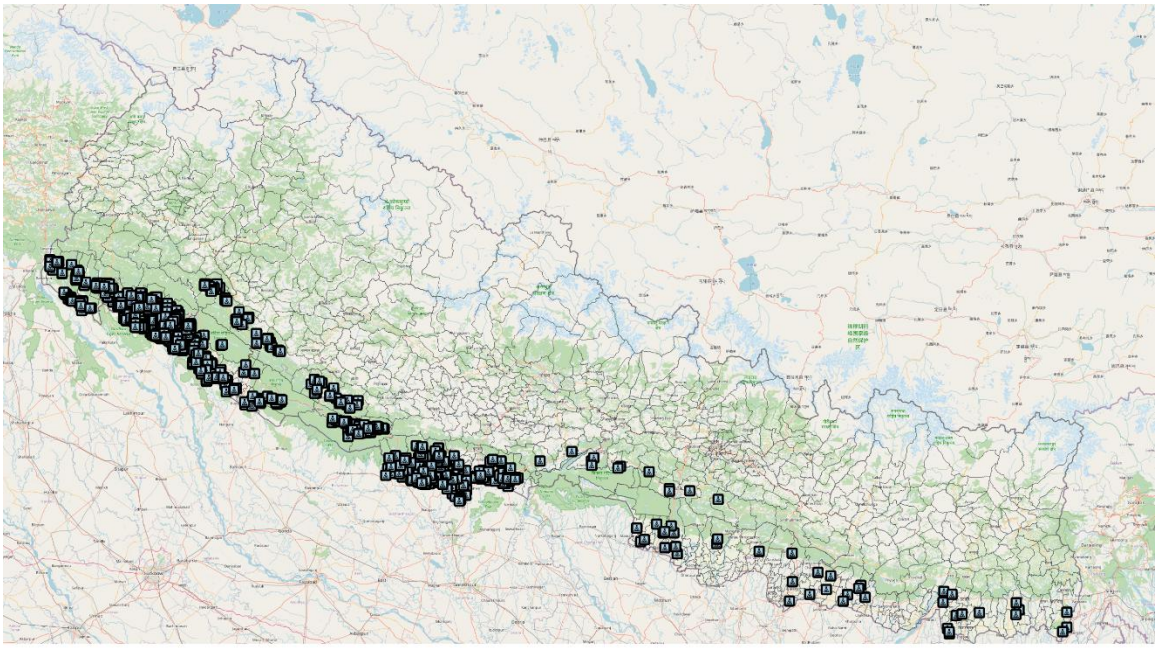

Figure 4 Sampled machinery locations across Nepal's lowland and mid-hill regions.

1.2.3 Co-variates

A review of factors that determine suitability of mechanization is reported in Table *1*. These include land features that restrict navigation and accessibility to land productivity.

1.2.3.1 Slope and elevation

Slope is important in determining the suitability of field-based mechanization in terms of accessibility and ease of navigation (Yang et al., 2023b). A general slope threshold for safe ploughing operation has been set at 15 degrees while adapted four-wheel tractors has potential to operate on slopes of up to 20 degrees (Grečenko, 1984b). A threshold of 8 degree (14%) has been set for 65hp tractor (Amongo et al., 2023b).

Farmlands have further been classified into 5 sub-slope mechanization potential categories as follows (Höfig and Araujo-Junior, 2015):

1) *Extremely Able (0 to 5%), which is ideal for mechanization, allowing for efficient machinery use.*
2) *Very Able (5.1 to 10%), which is still favorable, with minimal limitations.*
3) *Able (10.1 to 15%) which is suitable but may require careful management.*
4) *Moderately Able (15.1 to 20%) which is increasingly challenging for mechanization.*
5) *Not Recommended (>20%) which pose significant restrictions on mechanization.*

Elevation principally defines land suitability as it is associated with changes in bioclimatic conditions. It defines the production potential and suitability for a range of agricultural production systems, requiring different levels of mechanization.

Table 1 Co-variates used to determine mechanization suitability and thresholds from various sources

Variable	Criteria	Suitability Level	Thresholds	Sources
Slope	Degree of terrain slope	Highly Suitable Suitable	0%-5% 5.1% -10%	(Höfig and Araujo-Junior, 2015)
		Moderately Suitable	10.1%-15%	
		Marginally Suitable	15.1%-20%	
		Not Suitable	>20%	
Road Accessibility	Distance of the parcel to the nearest agricultural machinery			(Yang et al., 2023a)
	Road Network Proximity: Distance to nearest road	Highly Suitable	<100 m	(Amongo et al., 2023a)
	Degree of Road Compaction: Ration of road length in meters to a supported area in hectares	Most advantageous	35 m per ha	(Jasiński & Nowak, 1986, as cited in Grzywna & Rybicki, 2017)
	Road surface	Highly Suitable	Blacktopped	
		Moderately Suitable	Paved	
		Less Suitable	Unpaved/dirt	
Soil	Soil Texture	least fuel consumption	Loamy-sandy	(Oduma and Oluka, 2019)
		Moderate fuel consumption	Sandy-clay	
		High fuel consumption	Clay-loam	
Irrigation	Irrigation facility availability	Suitable	Area with Irrigation Scheme	(Tikawa et al., 2020)
		Less Suitable	Area without Irrigation Scheme	

1.2.3.2 Road proximity, density and surface

The presence and nature of a road influence machine suitability for a particular land parcel in various ways. Directly, distance between farm and road ensures that machinery reach the agricultural land and transported with ease to the repair service centers. A study in Philippines proposed <100 m as the most suitable distance from nearest road so that tractor can be transported to the field with low operational cost (Amongo et al., 2023b). In addition to proximity to major roads, the road density - the ratio of road length in meters to a supported area in hectares – has been used to indicate machine suitability. The sufficiency road density threshold is set at 35 m per ha (Jasiński & Nowak, 1986, as cited in Grzywna & Rybicki, 2017) although higher values may not only indicate very good access but potentially unsuitable non-farm land uses. Where non-farmland uses are identifiable such as high-density settlement parcels and market centers should be masked and excluded. However, other non-farm areas including fallow and forests should be included to estimate the potential for mechanization for not only farming but also the other land uses. Another important aspect is the road surface: the blacktop is the most suitable, followed by paved, and then unpaved/dirt roads for transportation purposes. Properly blacktopped or paved

roads are motorable but also are less damaged by erosion. Indirectly, road presence also provides access to markets making plots near the roads more productive and profitable, hence more suitable for mechanization (K.C., 2011).

1.2.3.3 Soil texture and fertility

Soil texture determines the suitability of machinery for efficient operation. Operation of machinery in clay-loam soil consumes the highest fuel followed by sandy-clay and least on loamy-sandy soil. Sandy-clay soil recorded the highest tyre slippage for all the implements, followed by loamy-sandy and the least tyre slippage was recorded on clay loam soil. However, all the implements in different soils recorded average wheel slippage below the top limit of wheel slippage (20 %), showing that the soils were trafficability (Oduma and Oluka, 2019). In addition, soil type influences investment decisions with more fertile soils having higher productivity and hence more suitable for mechanization (Alberti et al., 2018).

1.2.3.4 Water Availability

Irrigation availability increases cultivation which increases the demand of agricultural machinery. An study showed that highly irrigated areas with extensive water distribution networks will generally require a higher number of tractors to ensure efficient land cultivation and management, compared to areas with lower irrigation (Tikawa et al., 2020). So, we can rank the area with irrigation facilities available with more suitable for agricultural machinery than area without facility of agricultural machinery.

References

Alberti, G., Grima, R., Vella, N.C., 2018. The use of geographic information system and 1860s cadastral data to model agricultural suitability before heavy mechanization. A case study from Malta. PLOS ONE 13, e0192039. https://doi.org/10.1371/journal.pone.0192039

Amongo, R.M., Saludes, R., Gallegos, R.K., Relativo, P.L., Duminding, R.S., Pantano, A.D., Cunan, J.J.P., Lalap-Borja, G.N., 2023a. A GIS-based land suitability model for agricultural tractors in CALABARZON Region, Philippines. Sci. Rep. 13, 18272. https://doi.org/10.1038/s41598-023-45071-w

Amongo, R.M., Saludes, R., Gallegos, R.K., Relativo, P.L., Duminding, R.S., Pantano, A.D., Cunan, J.J.P., Lalap-Borja, G.N., 2023b. A GIS-based land suitability model for agricultural tractors in CALABARZON Region, Philippines. Sci. Rep. 13, 18272. https://doi.org/10.1038/s41598-023-45071-w

Berger, A., Della Pietra, S., Della Pietra, V., 1996. A maximum entropy approach to natural language processing. Comput. Linguist. 21, 39–71.

Devkota, R., Pant, L.P., Gartaula, H.N., Patel, K., Gauchan, D., Hambly-Odame, H., Thapa, B., Raizada, M.N., 2020. Responsible Agricultural Mechanization Innovation for the Sustainable Development of Nepal's Hillside Farming System. Sustainability 12, 374. https://doi.org/10.3390/su12010374

FAO, University of Bonn, 2021. Climate change impacts on twenty major crop pests in Central Asia, the Caucasus and Southeastern Europe. FAO; https://doi.org/10.4060/cb5954en

Grečenko, A., 1984a. Operation on steep slopes: State-of-the-art report. J. Terramechanics 21, 181–194. https://doi.org/10.1016/0022-4898(84)90020-X

Grečenko, A., 1984b. Operation on steep slopes: State-of-the-art report. J. Terramechanics 21, 181–194. https://doi.org/10.1016/0022-4898(84)90020-X
Grzywna, A., Rybicki, R., 2017. THE TECHNICAL PARAMETRS AND ROAD NETWORK IN THE JAKUBOWICE KONINSKIE VILLAGE. J. Ecol. Eng. 18, 95–99. https://doi.org/10.12911/22998993/74274
Gürgenç Irmakli, P., Aydin, A., 2022. Contribution of Land Consolidation to Agriculture and Agricultural Mechanization. Tekirdağ Ziraat Fakültesi Derg. 19, 582–599. https://doi.org/10.33462/jotaf.1033732
Höfig, P., Araujo-Junior, C.F., 2015. Terrain slope classes and potential for mechanization to coffee plantation in the state of Paraná. Coffee Sci. 10, 195–203. https://doi.org/10.25186/CS.V10I2.833
Jeon, J., Lavrenko, V., Manmatha, R., 2003. Automatic image annotation and retrieval using cross-media relevance models, in: Proceedings of the 26th Annual International ACM SIGIR Conference on Research and Development in Informaion Retrieval. Presented at the SIGIR03: The 26th ACM/SIGIR International Symposium on Information Retrieval, ACM, Toronto Canada, pp. 119–126. https://doi.org/10.1145/860435.860459
Kamau, H., Roman, S., Biber-Freudenberger, L., 2023. Nearly half of the world is suitable for diversified farming for sustainable intensification. Commun. Earth Environ. 4, 446. https://doi.org/10.1038/s43247-023-01062-3
Karasev, A., 2023. EXCURSION TO THE HISTORY OF TRACTOR BUILDING AND THE INTRODUCTION OF TRACTORS IN AGRICULTURE. Tekhnicheskiy Serv. Mashin 1. https://doi.org/10.22314/2618-8287-2023-61-1-155-163
K.C., K.B., 2011. Assessing rural resources and livelihood development strategies combining socioeconomic and spatial methodologies. Int. Res. J. Agric. Sci. Soil Sci. 1, 040–052.
Ministry of Agriculture and Livestock Development, 2014. Agriculture Mechanization Promotion Policy.
Mohanty, N., John, A.L.-St., Manmatha, R., Rath, T.M., 2013. Shape-Based Image Classification and Retrieval, in: Handbook of Statistics. Elsevier, pp. 249–267. https://doi.org/10.1016/B978-0-444-53859-8.00010-2
National Statistics Office, 2023. National Sample Census of Agriculture 2021_22 (National Report).
Oduma, O., Oluka, S., 2019. Effect of soil type on power and energy requirements of some selected agricultural field machinery in south-east Nigeria. Poljopr. Teh. 44, 69–77. https://doi.org/10.5937/PoljTeh1903069O
Paudel, G.P., Kc, D.B., Rahut, D.B., Justice, S.E., McDonald, A.J., 2019. Scale-appropriate mechanization impacts on productivity among smallholders: Evidence from rice systems in the mid-hills of Nepal. Land Use Policy 85, 104–113. https://doi.org/10.1016/j.landusepol.2019.03.030
Phillips, S.J., Anderson, R.P., Schapire, R.E., 2006. Maximum entropy modeling of species geographic distributions. Ecol. Model. 190, 231–259. https://doi.org/10.1016/j.ecolmodel.2005.03.026
Prasad, K.A., 2020. IMPACTS OF AGRICULTURAL MECHANIZATION: A CASE OF PALPA DISTRICT OF NEPAL. Acta Mech. Malays. 3, 16–19. https://doi.org/10.26480/amm.01.2020.16.19
Singh, G., 2006. Estimation of a Mechanisation Index and Its Impact on Production and Economic Factors—a Case Study in India. Biosyst. Eng. 93, 99–106. https://doi.org/10.1016/j.biosystemseng.2005.08.003
Takeshima, H., Justice, S.E., 2020. Evolution of agricultural mechanization in Nepal. International Food Policy Research Institute, Washington, DC. https://doi.org/10.2499/9780896293809_09

Tikawa, I.G.B., Tika, I.W., Gunadnya, I.B.P., 2020. Analisis Kebutuhan Traktor Berdasarkan Ketersediaan Air pada Subak di Kabupaten Tabanan. J. BETA Biosist. Dan Tek. Pertan. 8, 329. https://doi.org/10.24843/JBETA.2020.v08.i02.p17

Yang, H., Ma, W., Liu, T., Li, W., 2023a. Assessing farmland suitability for agricultural machinery in land consolidation schemes in hilly terrain in China: A machine learning approach. Front. Plant Sci. 14, 1084886. https://doi.org/10.3389/fpls.2023.1084886

Yang, H., Ma, W., Liu, T., Li, W., 2023b. Assessing farmland suitability for agricultural machinery in land consolidation schemes in hilly terrain in China: A machine learning approach. Front. Plant Sci. 14, 1084886. https://doi.org/10.3389/fpls.2023.1084886

cgiar.org/initiative/mixed-farming-systems