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EASTERN SHORE

UMES EXTENSION

AI for Agricultural Resiliency Among Socially Disadvantaged (SDA) and Underserved Farmers

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The findings and conclusions in this preliminary presentation have not been formally disseminated by the U.S. Department of Agriculture and should not be construed to represent any agency determination or policy.

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May 14, 2024

Soar Above and Beyond

USDA

Background

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- The Agriculture Improvement Act of 2018 (2018 Farm Bill) includes provisions that address the unique circumstances and concerns of socially disadvantaged, beginning, limited resource, and veteran farmers and ranchers ("historically underserved producers").

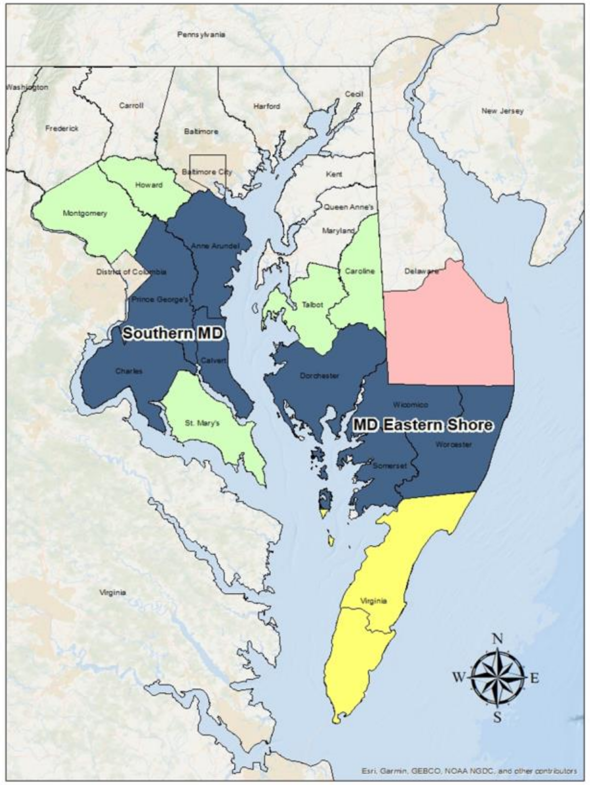
- Since the outbreak of COVID in 2020, a significant increase among socially disadvantaged and underserved audiences (young and old) expressing interest in farming as a means to provide supplemental income and addressing food insecurity.

- Many of these farmer groups generally lack **adequate farming experience, have little start-up capital,** and **limited access to financial credit and land**.

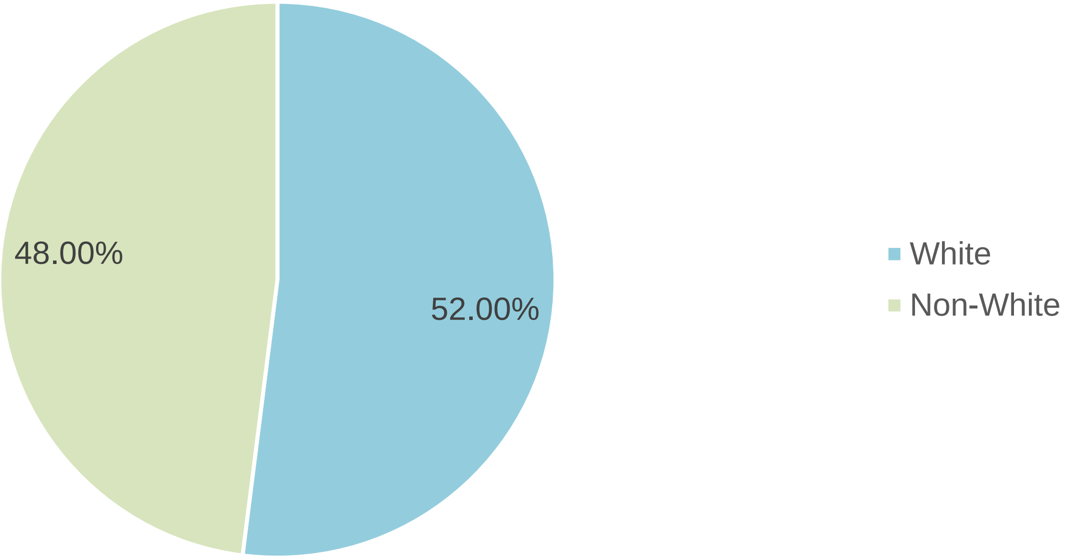
Background

The University of Maryland Eastern Shore (UMES) Extension conducted a farmers' needs assessment in agriculture (FNAA) in 2021/2022.

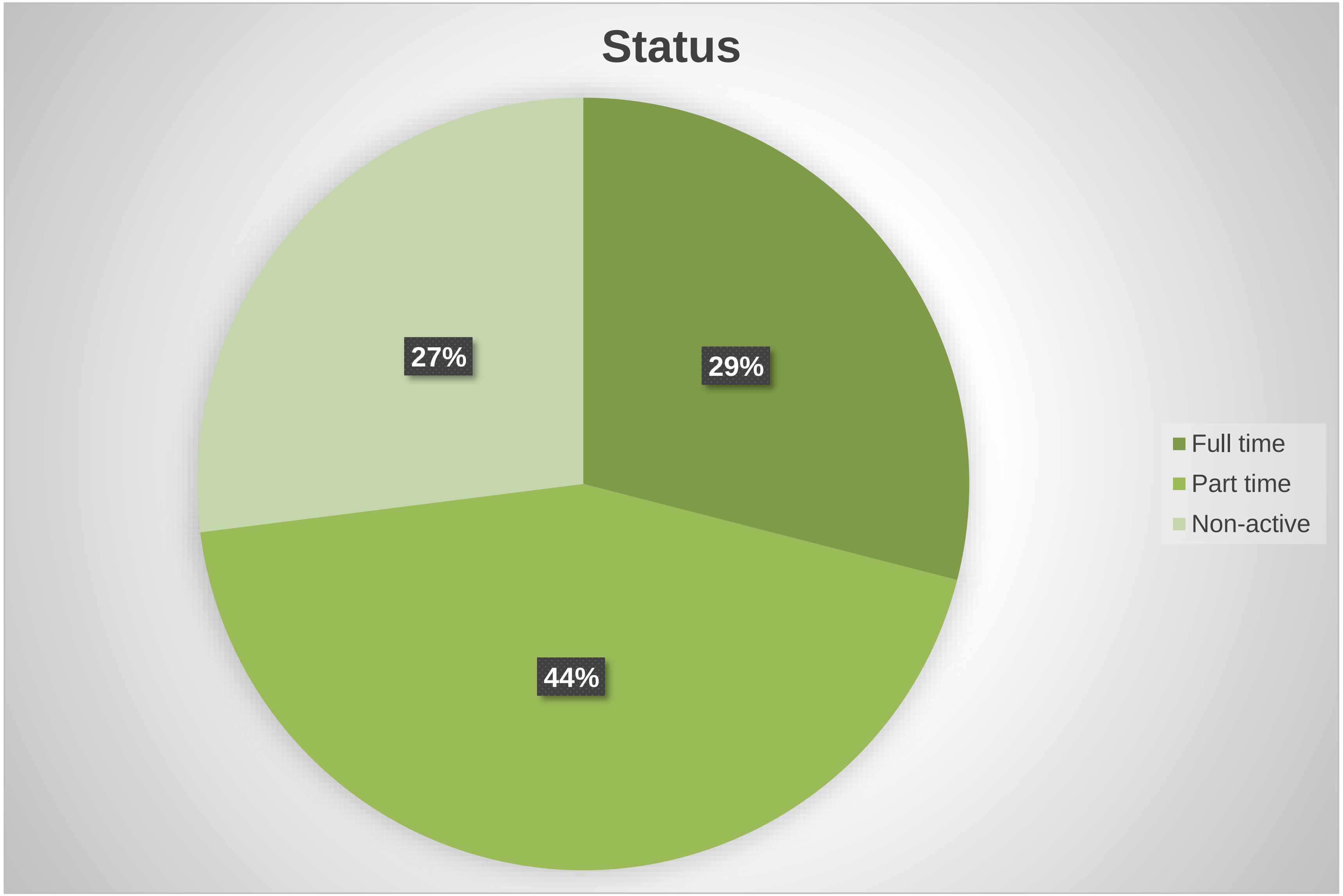
The solitary goal of FNAA was to optimize the desired impact of Extension programs on the socio-economic and environmental benefits of the target audience.



(FNAA) in 2021/2022 (124 Individuals)



Background



Background

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Based on the data collected, farmers reported a variety of problems associated with farming, which were grouped into three tiers based on the percentage of responses.

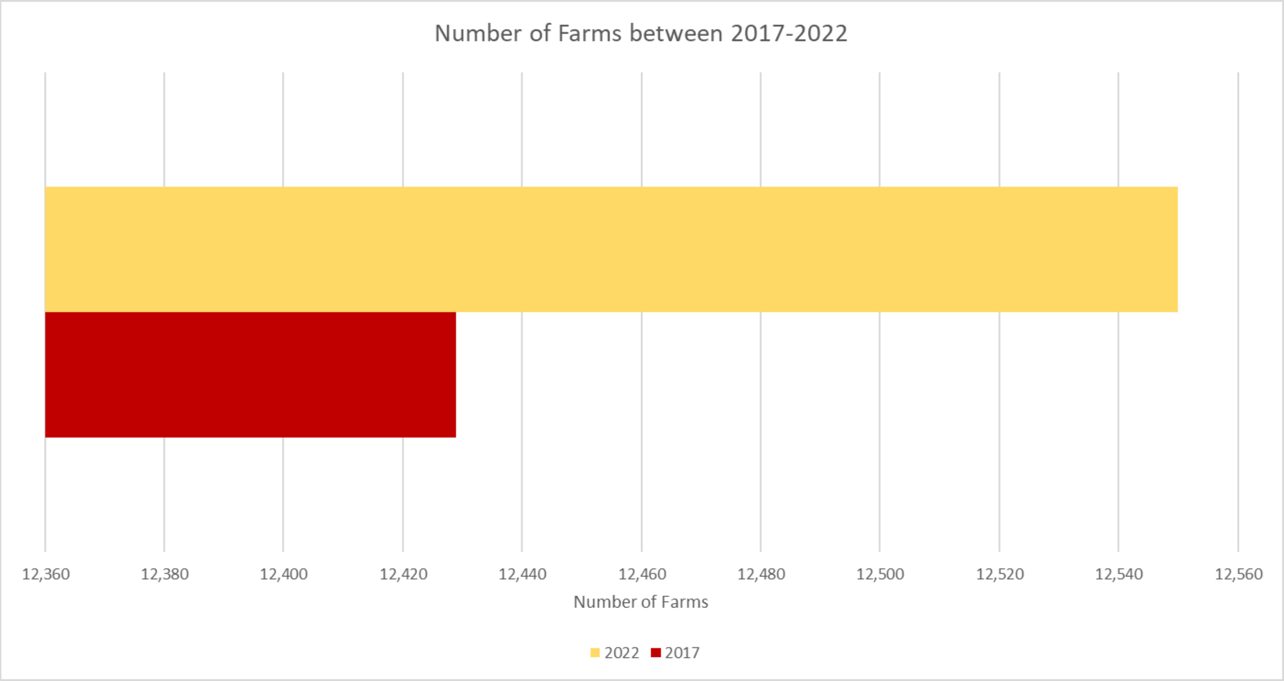
The top challenges identified in Tier 1 included: lack of capital (93%), followed by expensive production inputs and a shortage of labor (92%).

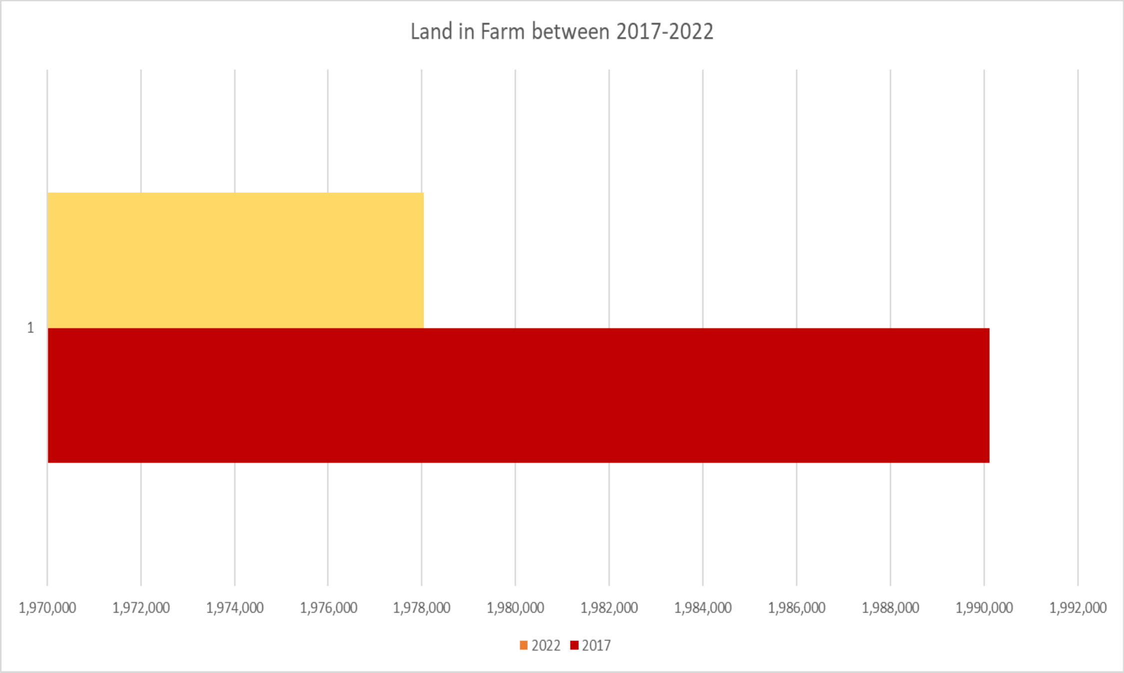
In tier 2, the following reoccurring themes that surfaced at 90% were: lack of produce-processing facilities; high-interest on credit; lack of access to market outlets; and the lack of computer knowledge and skills.

Tier 3 rounded out with a lack of farm business planning skills (88%) as being one of their chief concerns.

Key Challenges: Overview of unique barriers they face (e.g., financial, technological, educational).

Maryland Farms





Additional 121 Farms

Lost farm lands: 12,086 acres

Maryland’s Population

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Total Population (2020):

6,177,224

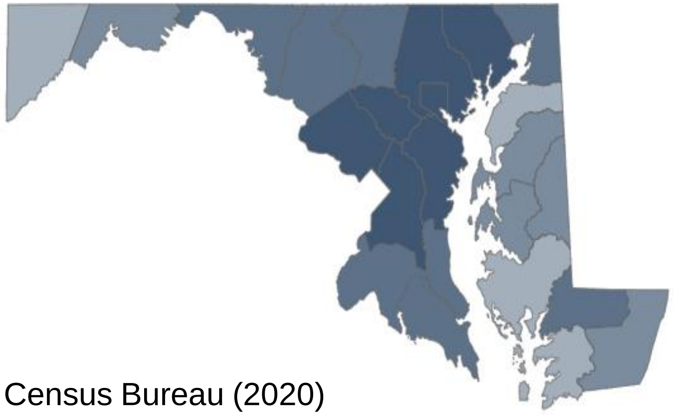
Numeric Change in Population (2010–2020):

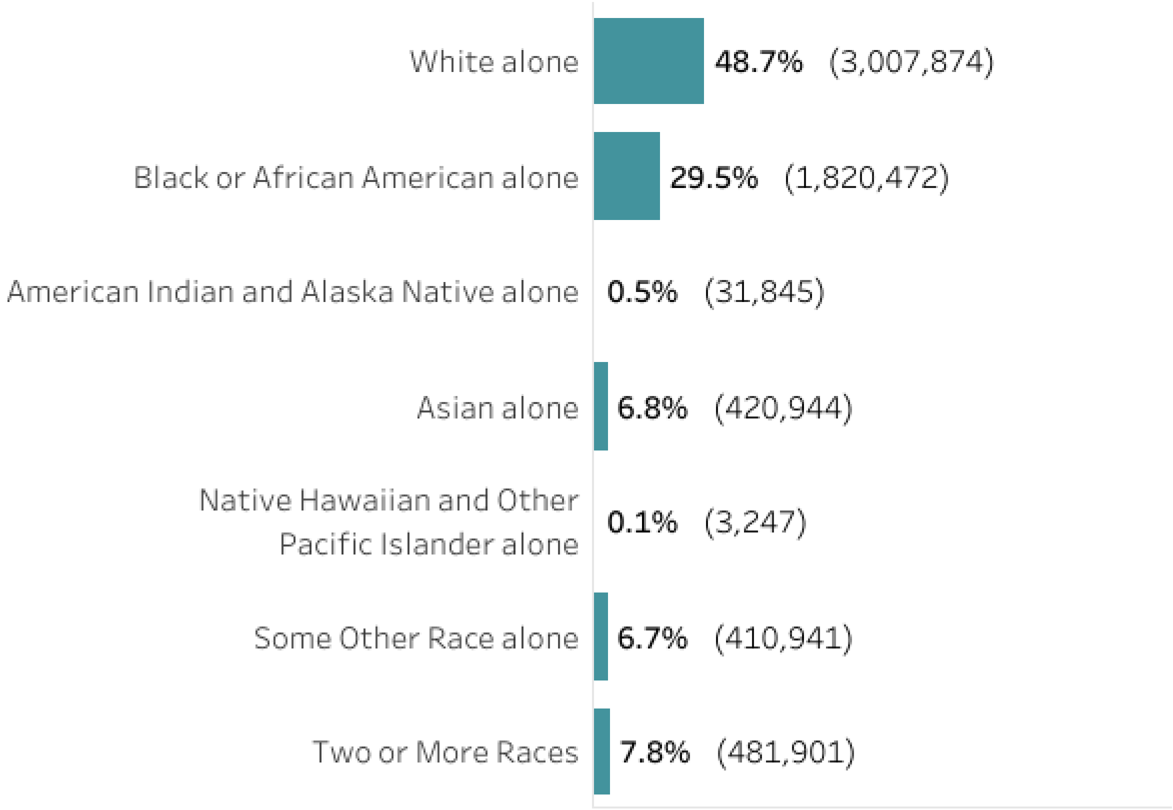
403,672

Percent Change in Population (2010–2020):

7.0%

Population Density in Maryland Counties: 2020





Source: U.S. Census Bureau (2020)

Farm Ethnicity Representation in Maryland

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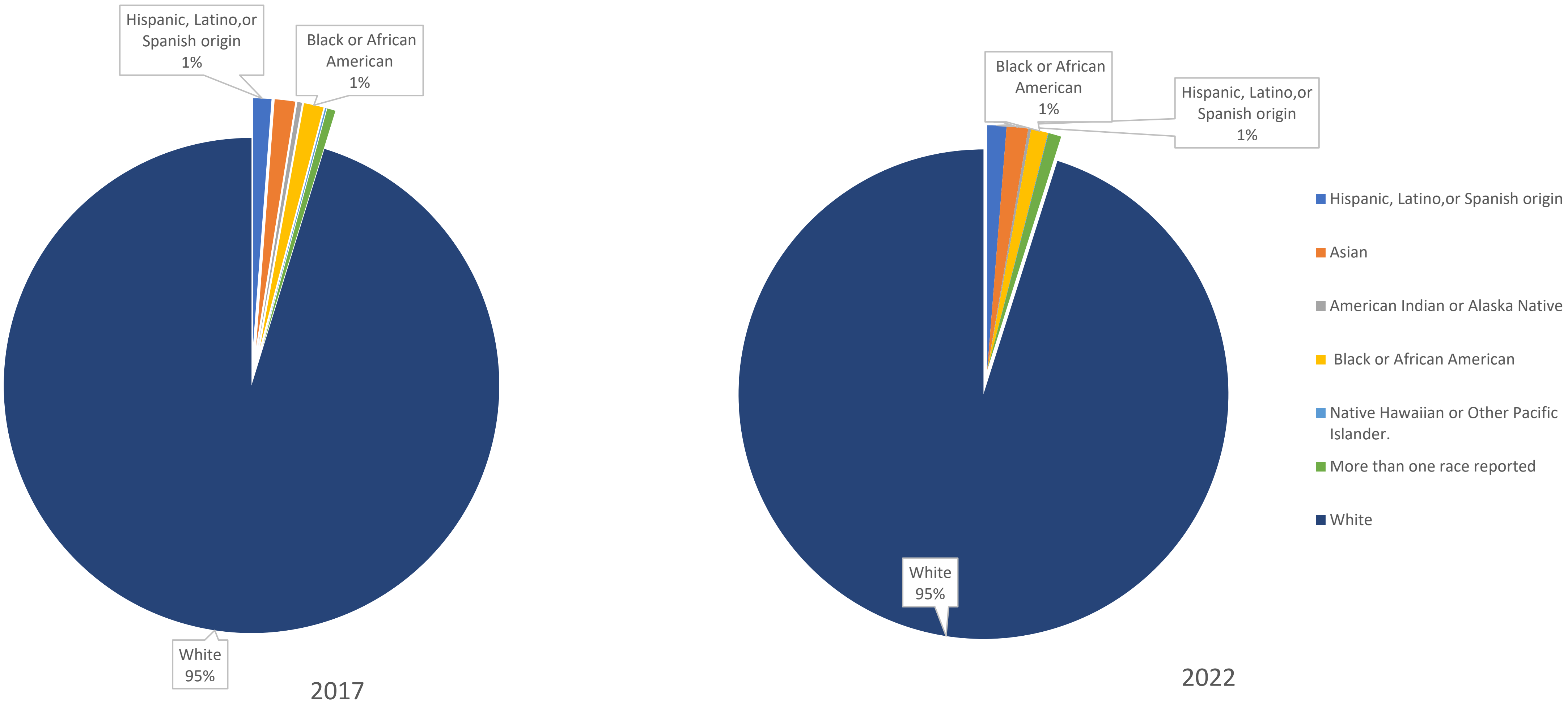
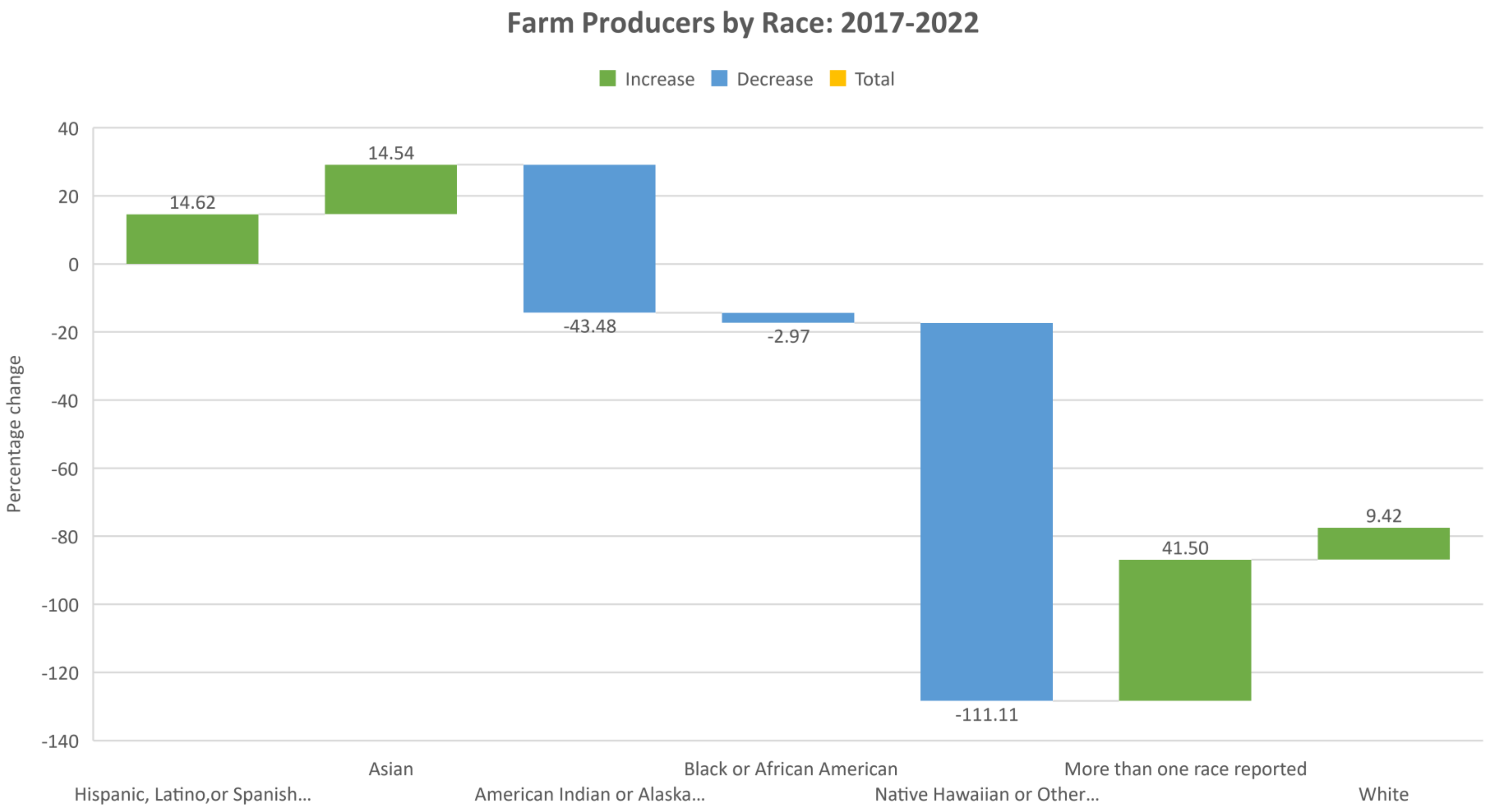


Farm Producers: Maryland



Farm Producers: Maryland

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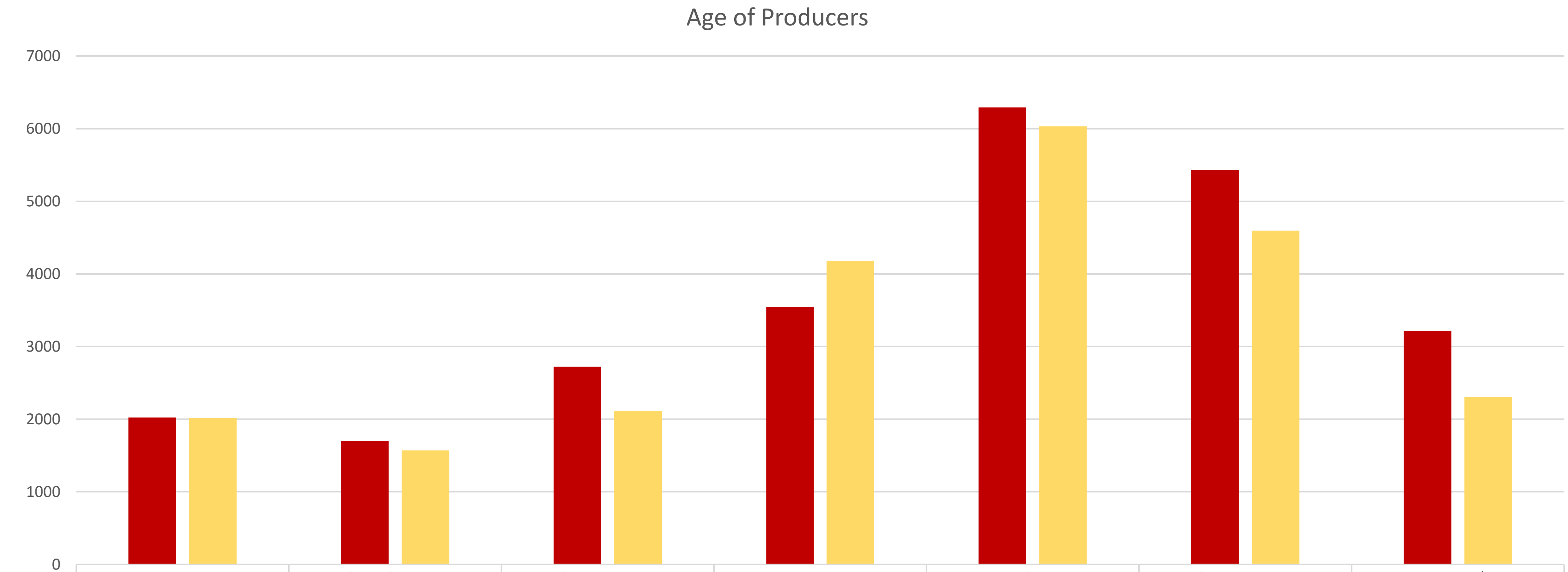

	Age	25 to 34 years	35 to 44 years	45 to 54 years	55 to 64 years	65 to 74 years	75 years and over ....
Series1	2022	1,701	2,721	3,545	6,293	5,431	3,216
Series2	2017	1,569	2,116	4,182	6,033	4,596	2,305

Farms by size: Maryland

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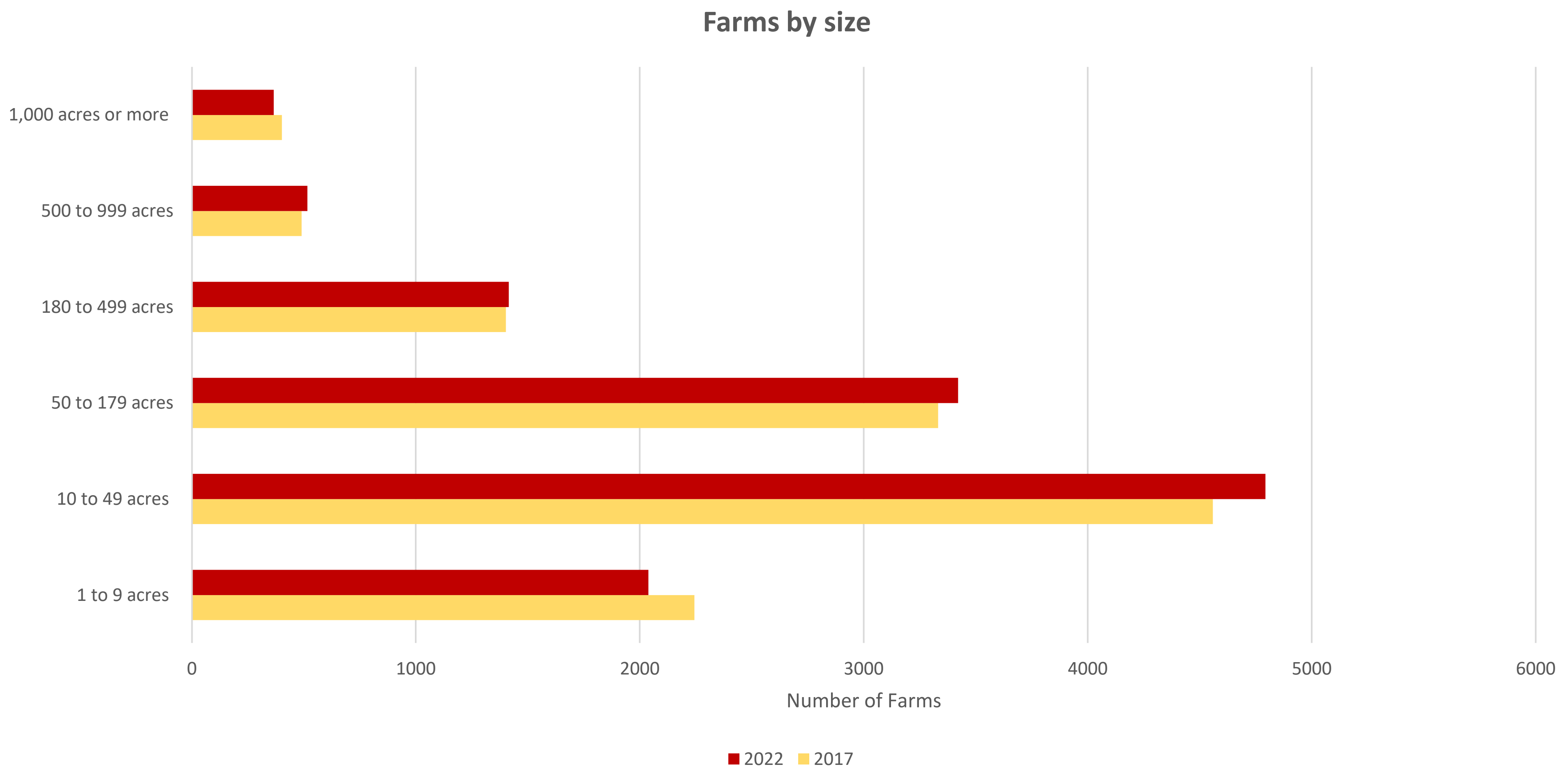
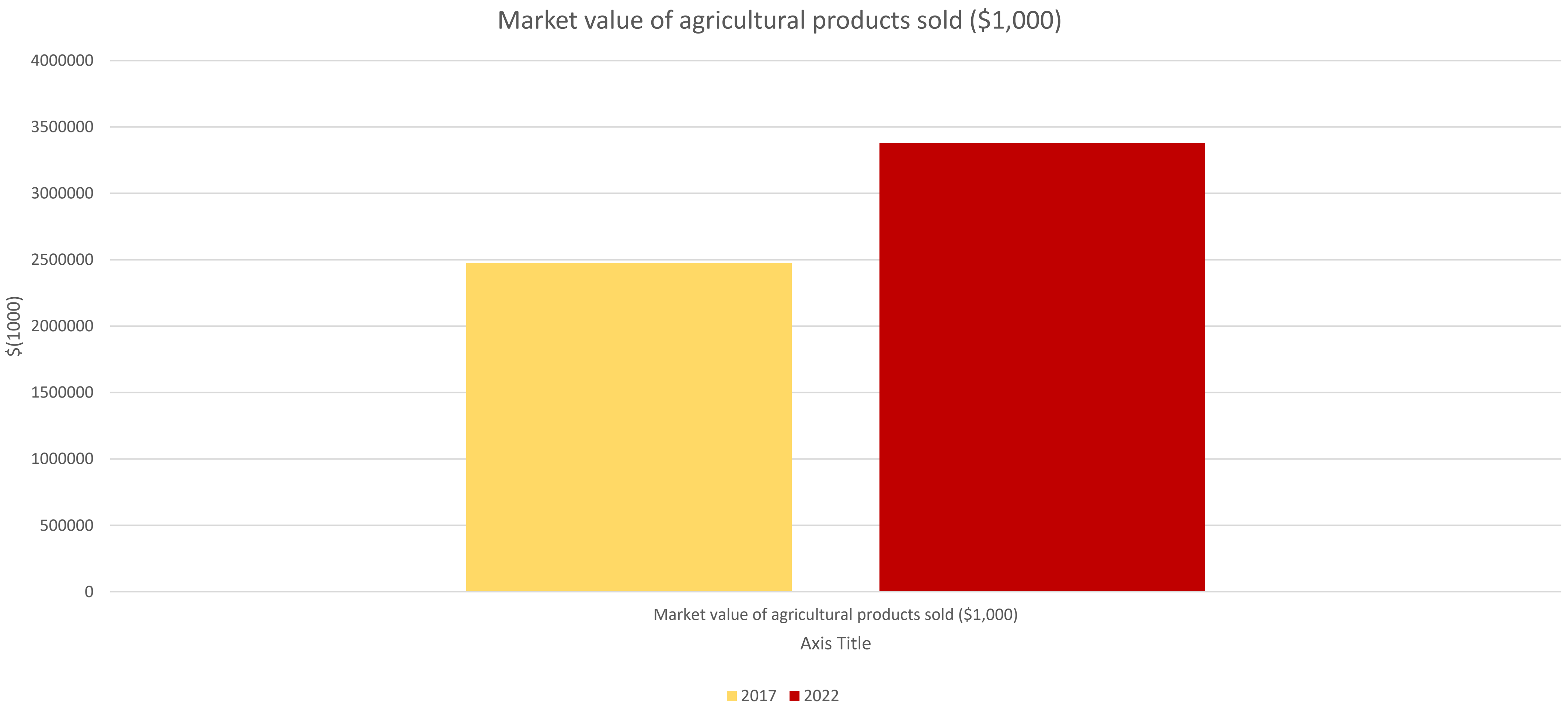


Market value of agricultural products sold in Maryland



Challenges in Agriculture for SDA and Underserved Farmers

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Particularly vulnerable to climate change. Low capacity to adapt to environmental changes.

Often located in marginal landscapes (hillsides, deserts, or floodplains), and exposed to a variety of climatic hazards (J.F Morton, 2007; FAD,2013)

Tend to rely on crops negatively impacted by climate change in terms of suitability (Hannah et al., 2016) and productivity (Lobell et al., 2008)

Often marginalized from social and development assistance programs (Vorley et al., 2012; Harvey et al., 2014), and are exposed to the unpredictability in the prices of commodities due to direct competition with industrial-scale farming (Morton, 2007).

Challenges in Agriculture for Small and Midsize Farms

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Due to its high cost (Kosior, 2017; Sch¨onfeld et al., 2018; Mark, 2019), AI is usually deployed on large monoculture farms (Carbonell, 2016) or high-value crops (Shapland, 2021) even though most agriculture occurs on small and midsize farms (USDA, 2017).

Based on the 2017 Census of Agriculture, an increasing number of female farmers, first-generation farmers, and American Indian farmers are key players in modern agriculture.

The innovations developed by AI need prioritization to enable AI methods for the 98% of US farms that are family-owned (i.e., operated by individuals related to the owner) and, in particular, the 94% of all farms that are classified as small and midsize, which account for over 40% of the value of total agricultural production (Kassel & Morriso, 2020).

Implementing Foundational AI Solutions for Small and Midsize Farms

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- Climate variability profoundly affect small and midsize farms as growing cycles shift and water access changes. Ninety five percent of all American farms are small or midsize, producing less than $350,000 and $350,000 to $999,999 in gross cash income, respectively (USDA, 2017).

- Although small and midsize farms control 67% of the domestic farmland base, they have fewer resources to adapt to climate variability than large-scale Farms.

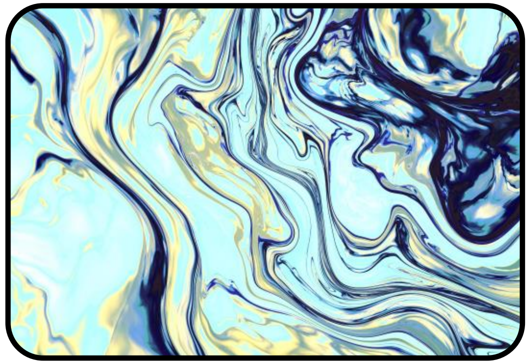
- Example: Adaptive crop scouting (i.e., detecting disease, insect or weed outbreaks, or water system failures that lead to crop loss) is essential for the success of small and midsize farms (Luna & House, 2020) as they are subject to climate change.

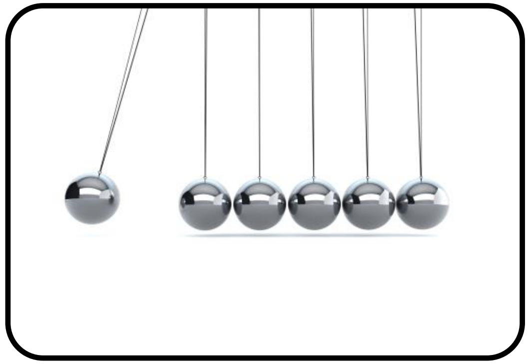
- Environmental sensors and remote sensing devices for crop monitoring have created an immense data flow that needs to be transferred into practical tools for farm management (Taechatanasat & Armstrong, 2014).

- Developing AI tools that are invisible to the user and streamline the detection and reporting of temporal change will greatly advance the quality of agricultural scouting and the adoption of smart technologies for farm management (DeClerq et al., 2022).

- By accessing real time data (e.g., climate data, hydrologic data) and data from sensors (e.g., climate, soil, plant), management models can retain complexity and accuracy while limiting manual data input by users (G. M, E. A, & Thompson, 2020.)

Foundational AI in Agriculture





Scientific Spatio-Temporal AI

Physics-Aware AI

Human-in-the-Loop AI

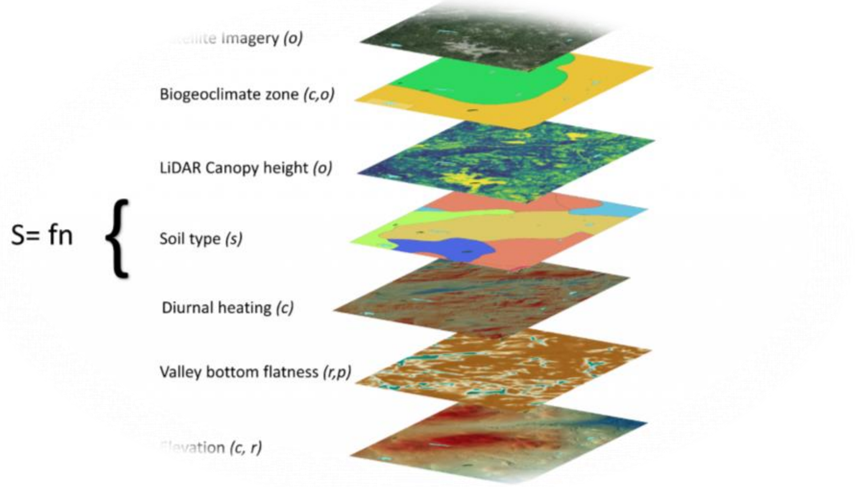
Resource-Efficient AI

Spatio-Temporal AI

- Traditional statistical approaches are unable to handle high dimensional data which feature multi-scale structures in space and time, or data with complex long-term dependencies.

- Modern AI-driven techniques are promising to overcome these limitations. In particular, deep learning (DL) (LeCun et al., 2015) techniques have demonstrated their ability to handle high dimensional spatio-temporal problems (Tran el at., 2015; Jain et al., 2016; Qiu et al., 2017; Kamilaris & Prenafeta-Bold´u, 2018; Wang & Yu, 2020).

- These next-generation AI models have the ability to improve nowcasting and seasonal forecasts of complex and multi-modal spatio-temporal data and better exploit rich multi-scale spatio-temporal structures.



Physics-Aware AI

Knowledge of physics and other domain-specific factors are widely ignored in typical AI algorithms. This contrasts sharply with scientific computing (Kincaid et al, 2009; Oberkampf & Roy, 2010; Wilson et al., 2014; Heath, 2018) where it is common to motivate and constrain problems by meaningful physical models and assumptions.

Physics-aware learning has recently emerged as a topic of interest in the Machine Learning (ML) community (Willard et al., 2020; Karniadakis et al., 2021; Kashinath et al., 2021). These physics-aware methods are constrained by the structure of the data and knowledge of the domain from which the data originates, as opposed to abstract theoretic considerations.

Physics-temporal AI models that rely on prior knowledge and incorporate domain-specific assumptions about the physical problems at hand extract information from small amounts of data and reduce uncertainty. Further embedding physical constraints into models improves their interpretability and the explainability, thus leading to more trustworthy predictions.

Human-in-the-Loop AI

Human users often do not trust state-of-the-art AI technologies due to the black-box structure of DL methods and unpredictable failure modes (Adadi & Berrada, 2018; Arrieta et al., 2020; Toreini et al., 2020).

Time-consuming expert annotation necessary for DL network training (Waldrop, 2019) is an additional barrier for human users. The representation that embed expert knowledge that drives decision-making processes into AI tool with few annotations is highly desired.

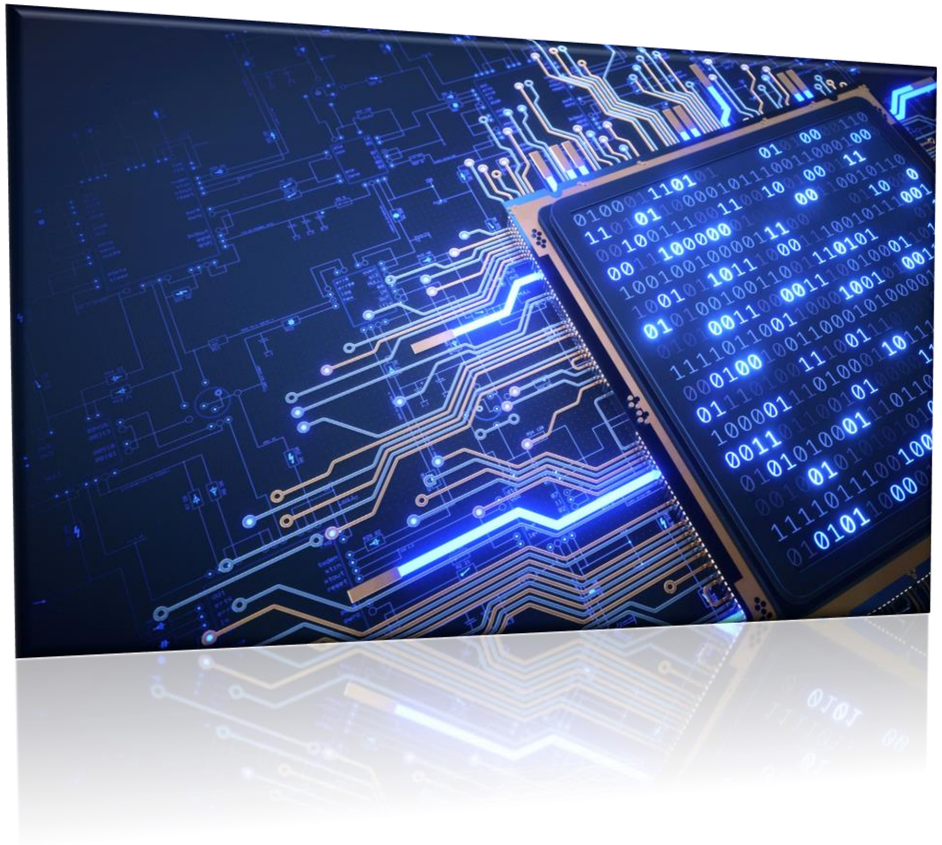
AI algorithms that humans understand and trust, as well as algorithms that can advantageously use expert knowledge while avoiding burdening the human with interaction requirements, are necessary.

Resource Efficient AI

Methods that overcome scarcity of power and memory resources typical of edge devices (e.g., drones or sensors) while performing inferences and training as needed in the field. To generate power and memory efficient algorithms for inference, training, and data collection on edge devices.

AI models that learn representations to enable knowledge transfer and the development of models from limited data. Enabling AI in user-inspired applications involves overcoming the limitations on two key resources: data and computation.

Automate the distinction between irrelevant change (e.g., seasonal, lighting, cloud cover, sensor change, imaging distance change) and relevant change (e.g., flowering, growth, rot, dehydration, weeds). Enable quantification of the frequency of anomalies.



AI key end-user products

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Integration of foundational AI methods to inform AI-based decision support tools for farm management and planning. The augmented decision support tools will enable farmers to make farm decisions at short and long term time scales on production practices, crop selection, and production inputs.

These tools will enable farmers to make effective short term decisions and support long term risk mitigation and resilience to climate changes.

To connect decision support tools to web services (e.g., satellite imagery, real time forecasts, and retrospective climate data) with sensors and drones providing real time data (e.g., climate, soil moisture, disease, pests) (G. M, E. A, & Thompson, 2020.)

Innovative data collection technologies such as advanced sensor types and edge computing technology to support sensors and drones. Explainable AI methods to determine which spatio-temporal features are most relevant for model predictions by representing and learning temporal patterns from appearance, sensor readings, and annotations.

Ag Econ Smart (AES): A Suite of Agricultural Economics Online Tools

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The Spatially Explicit Forest Ecological Assessment (SEFEA) Decision Support Tool

- Assess the consequences of management/planning choices.
- Explore effects of land use change on forest and watershed scales.
- Prioritize areas for land use, aiming at the maintenance of the forest and ecological resources and biodiversity.

Spatial Economic Decision Support (SEDS) Tool to Aid in Sustainable Agritourism

- Formalize, record, and refine agritourism decision-making process.
- Access agritourism information to improve farm profitability, consumer experience and policy making.

Making Smart Decisions with Enterprise Budgets

- Forecasting economic variables for a farm enterprise.
- Assist to make short and long-run decisions on a individual farm enterprise basis.

Marketing Strategies for the Farm Crops

- Three Cs of marketing
  - Customers, costs, and competition
- Four Ps of marketing
  - Product, price, place, and promotion

The Spatially Explicit Forest Ecological Assessment (SEFEA) Decision Support Tool Ecological Assessment (SEFEA) Decision Support Tool

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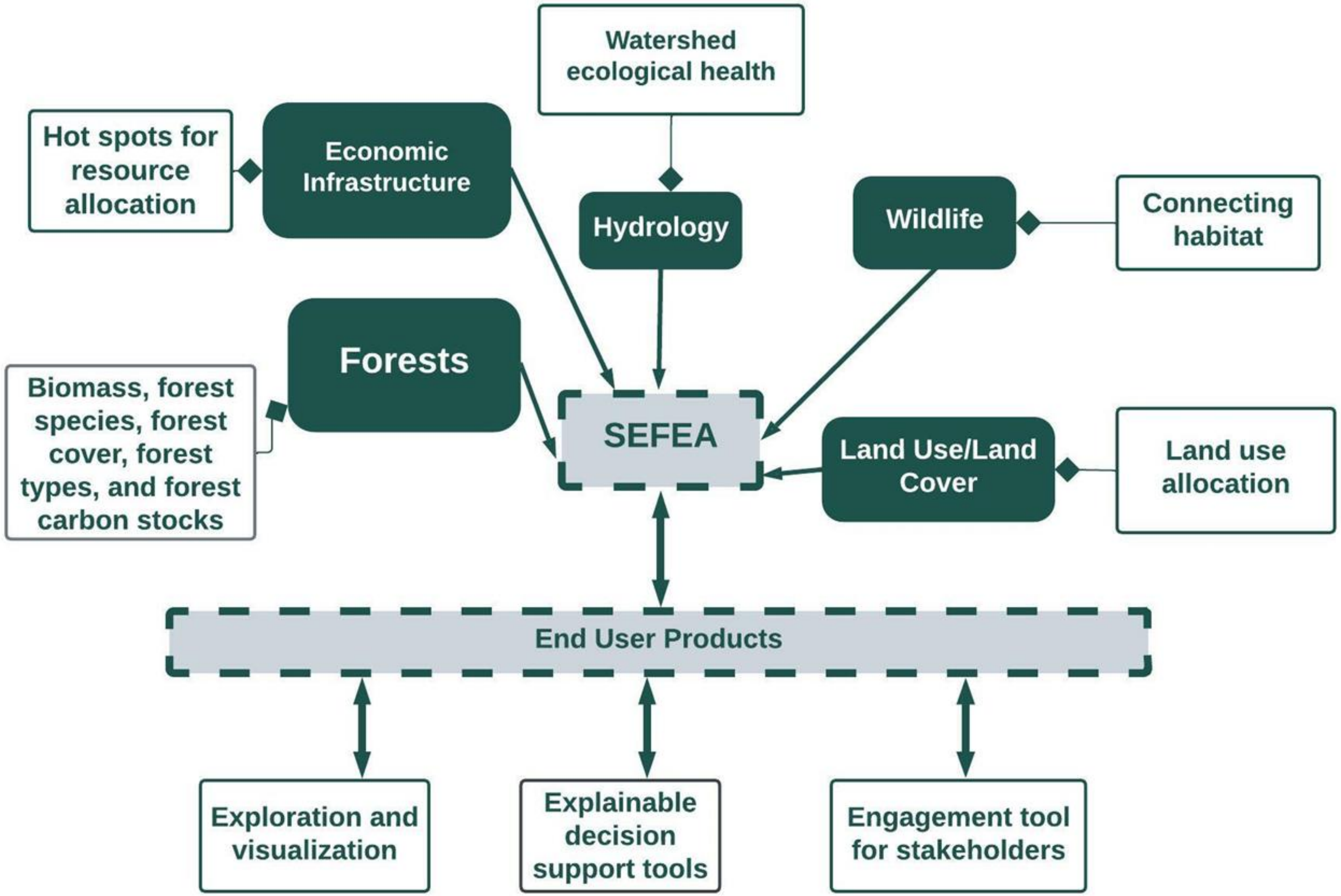
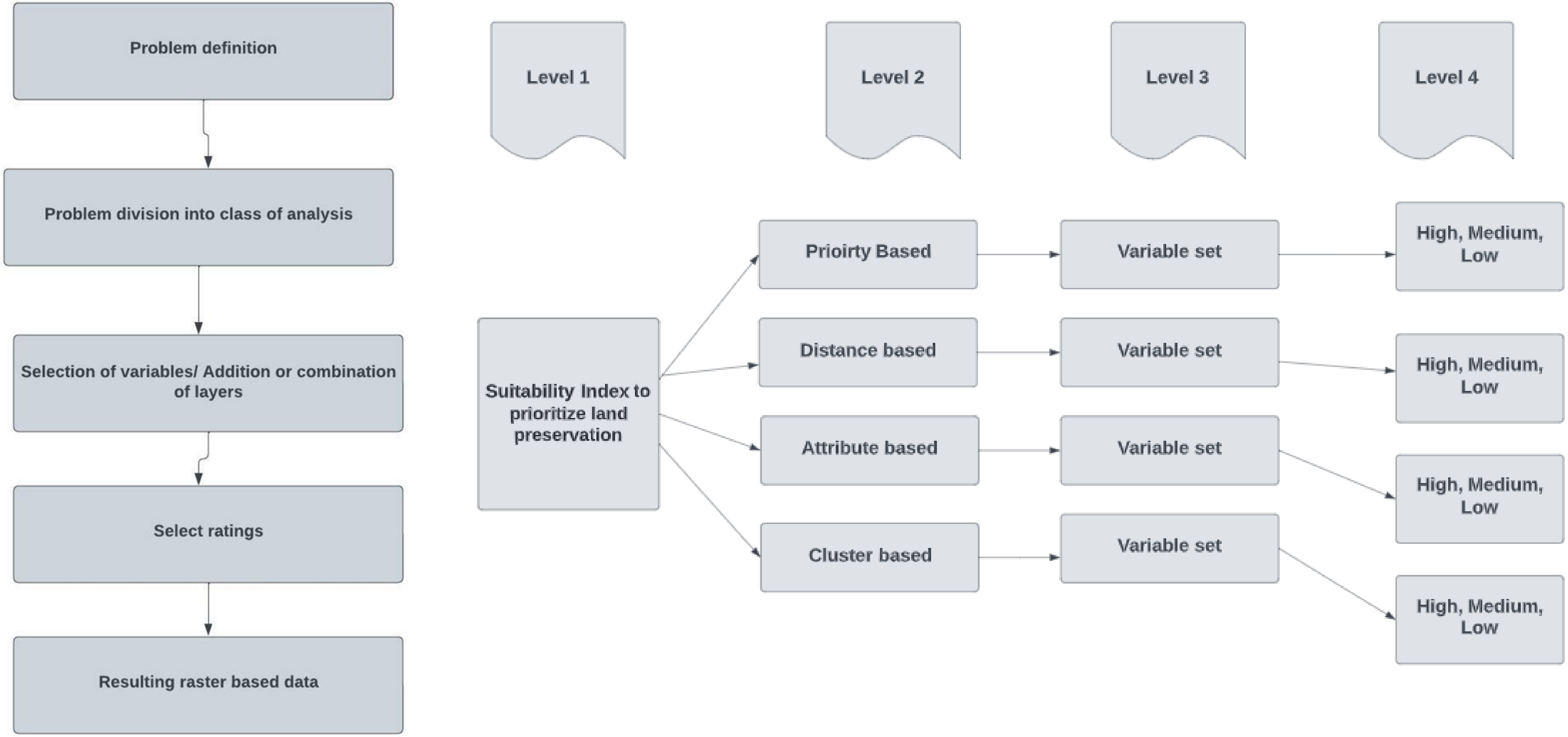
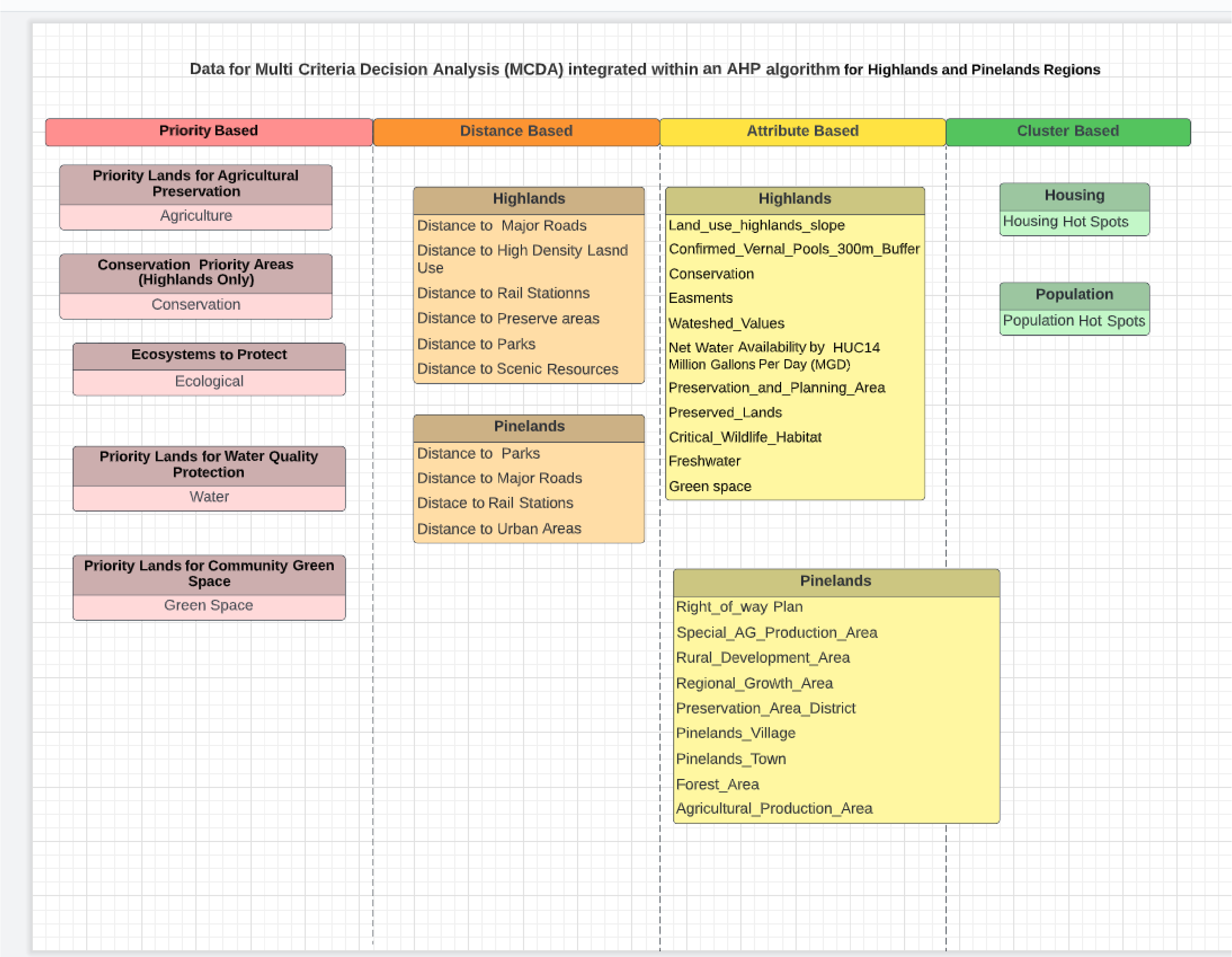




Analytical Hierarchy Process (AHP) analysis (ranked based scenarios)



Data for Multi Criteria Analysis (MCDA) integrated within an AHP Tool

Spatially Explicit Forest Ecological Assessment

- Assessment Area
- Scenario Assessment of LU Change Potential
- Watershed Ecological Health
- Boundary Layers
- AHP Tool
- Import Data
- Basemap
- Find Location
- Save / Share / Print
- Legend

<< Collapse

Legend

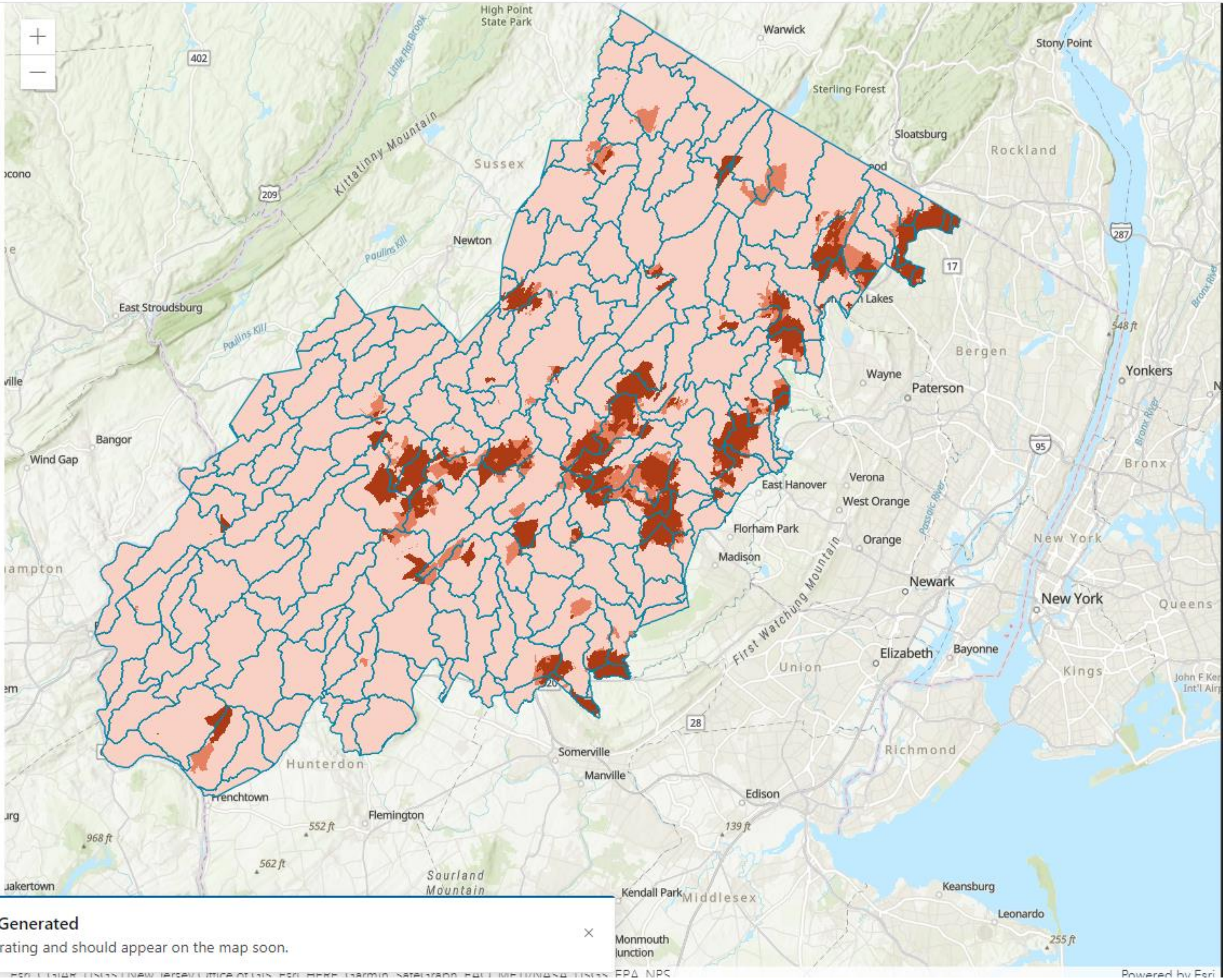
The Legend for the map.

Watershed HUC14

AHP Results 2022-09-27T14:10:22.386Z

Importance

- Low
- Medium
- High
- Unknown Value

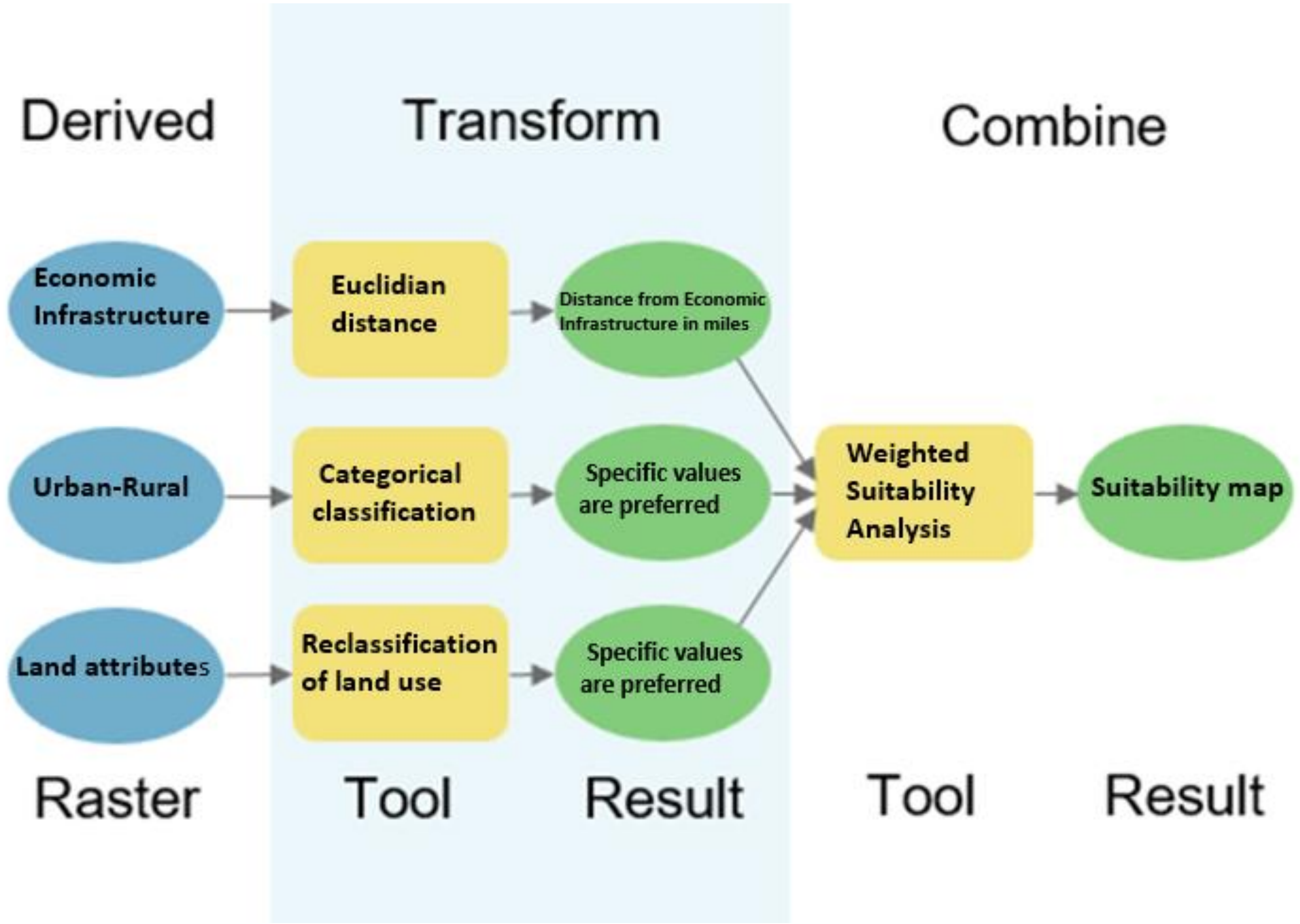


Raster Request Generated

Your raster is generating and should appear on the map soon.

Spatial Economic Decision Support (SEDS) Tool to Aid in Sustainable Agritourism

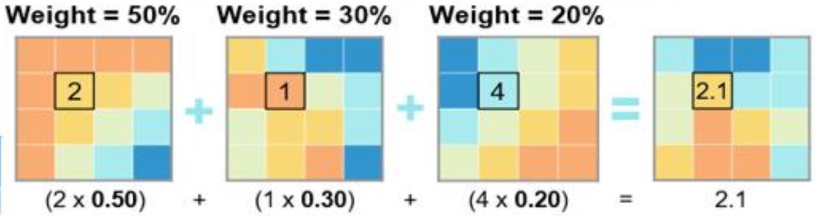
Spatial Economic Decision Support (SEDS) Tool to Aid in Sustainable Agritourism



Spatial Economic Decision Support (SEDS) Tool to Aid in Sustainable Agritourism

		Higher is better	Cheaper is better	Closer is better
Collect data	Agritourism site	Quality	Price ($)	Distance (m)
	Farm attributes	8	3.7	60
	Amenities	5	2.75	400
	Transportation routes	9	4.2	550
	Access to preferred area	1	2.5	350
	Minimum	1	2.5	60
	Maximum	9	4.2	550

Indicate your preferences



Normalise data

	Agritourism site	Quality	Price	Distance
Rank data	Farm attributes	0.88	0.29	1.00
	Amenities	0.50	0.85	0.31
	Transportation routes	1.00	0.00	0.00
	Access to preferred area	0.00	1.00	0.41

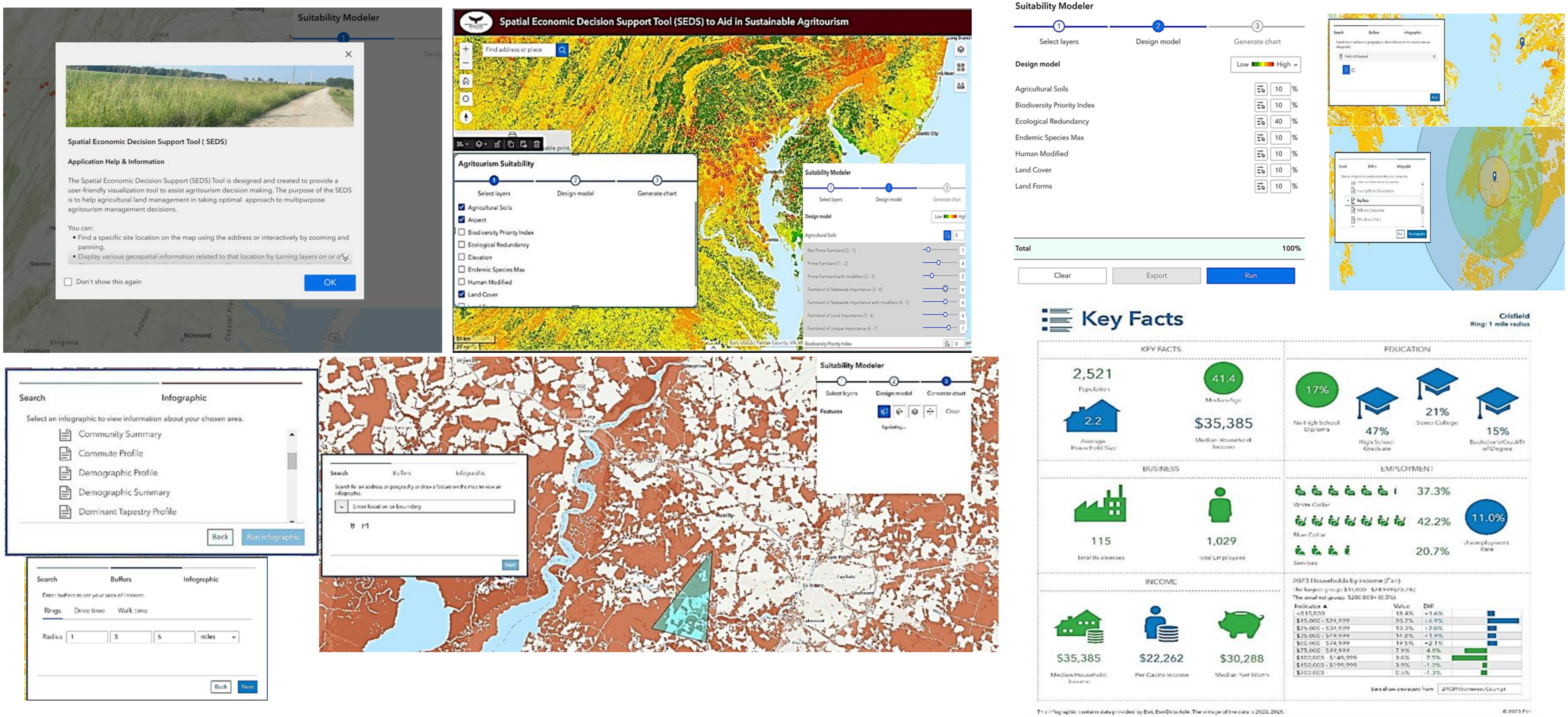
*Add Indicators * Weights*

Specify weights

Apply weights	Weights	2	1	1.5

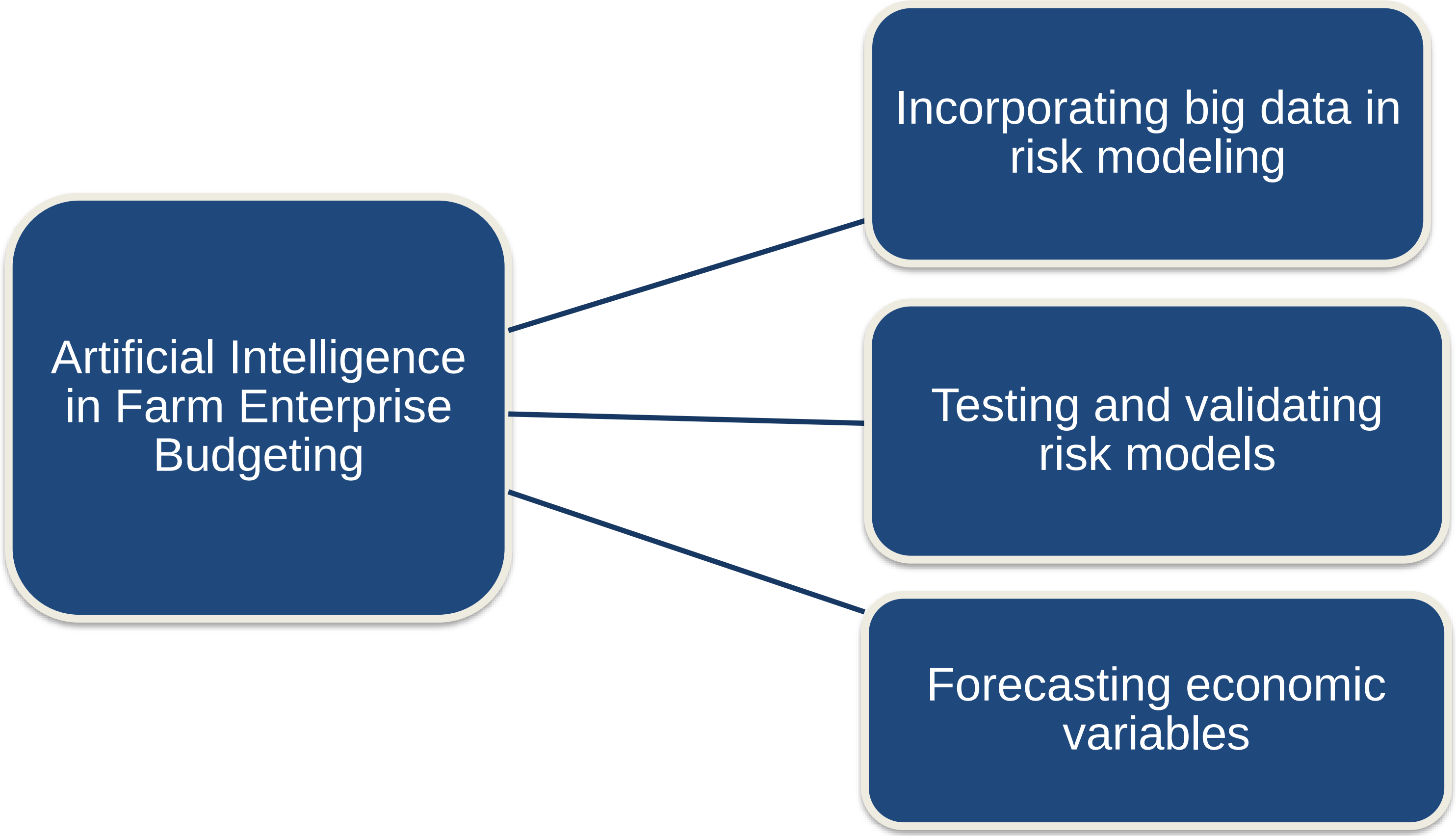
	Agritourism site	Score
Final score	Farm attributes	3.54
	Amenities	2.31
	Transportatio n routes	2.00
	Access to preferred area	1.61

Spatial Economic Decision Support (SEDS) Tool to Aid in Sustainable Agritourism



Farm Enterprise Budgeting

Farm Enterprise Budgeting



Type of Farm Enterprise Budgets

Traditional Crops and Livestock Production

- Very detailed, more accurate
  - Examples
    - Field corn, soybeans, dairy, hay
    - A simple search of “Enterprise Budget “crop” Extension”
    - 2023 Field Crop Budgets at UMD Extension website

Specialty crops

- Less detailed, less accurate because of differences in regions and inputs
  - Examples
    - Organics, niche crops, rotational grazing, value-added activities

CORN GRAIN, NO TILL, NONIRRIGATED PER ACRE FOR 2023				
ITEM	UNIT	QUANTITY	PRICE	TOTAL
GROSS INCOME				
CORN GRAIN	BUSHEL	160	$5.97	$955.20
VARIABLE COSTS				
SEED RR + Bt	1000 SEEDS	30	$3.48	$104.40
SOIL TEST	ACRE	1	$0.50	$0.50
NITROGEN	POUND	160	$0.95	$152.53
PHOSPHATE	POUND	30	$0.91	$27.40
POTASH	POUND	60	$0.54	$32.60
LIME	TON	0.5	$57.00	$28.50
GRAMOXONE SL 3.0	PINT	1.5	$0.87	$1.31
CORVUS	OUNCE	4	$6.01	$24.04
ATRAZINE	QUART	0.5	$6.03	$3.02
ROUNDUP (POST)*	QUART	1	$12.67	$12.67
PRINCEP	QUART	1	$5.92	$5.92
CROP INSURANCE (RP 70%)	ACRE	1	$20.23	$20.23
DRYING FUEL	BUSHEL	160	$0.36	$57.60
INTEREST ON OPERATING CAPITAL	$386.96	0.5	8.5%	$16.45
TOTAL VARIABLE COSTS LISTED ABOVE				$487.16
FIXED/OVERHEAD COSTS (CUSTOM RATES ARE USED AS A PROXY FOR FIELD OPERATION COSTS)				
FERTILIZER SPREADING	ACRE	1	$9.55	$9.55
NO-TILL PLANTING WITH FERTILIZER	ACRE	1	$23.81	$23.81
NITROGEN APPLICATION	ACRE	1	$11.61	$11.61
PESTICIDE APPLICATIONS	ACRE	2	$10.50	$21.00
HARVESTING	ACRE	1	$37.57	$37.57
HAULING	BUSHEL	160	$0.20	$32.00
INTEREST ON SPRING CUSTOM CHARGES	$65.97	0.5	8.5%	$2.80
LAND CHARGE	ACRE	1	$110.00	$110.00
TOTAL FIXED COST LISTED ABOVE				$248.34
TOTAL VARIABLE AND FIXED COST LISTED ABOVE				$735.50
NET INCOME OVER VARIABLE & FIXED COSTS LISTED ABOVE				$219.70

ANALYSIS	
BREAKEVEN	$4.60
VARIABLE COSTS PER UNIT	$3.04
OVERHEAD COST PER UNIT	$1.55
TOTAL COST PER UNIT	$4.60
PROFIT PER UNIT	$1.37

Source: 2023 Field Crop Budget at University of Maryland Extension website

Marketing : SWOT Analysis

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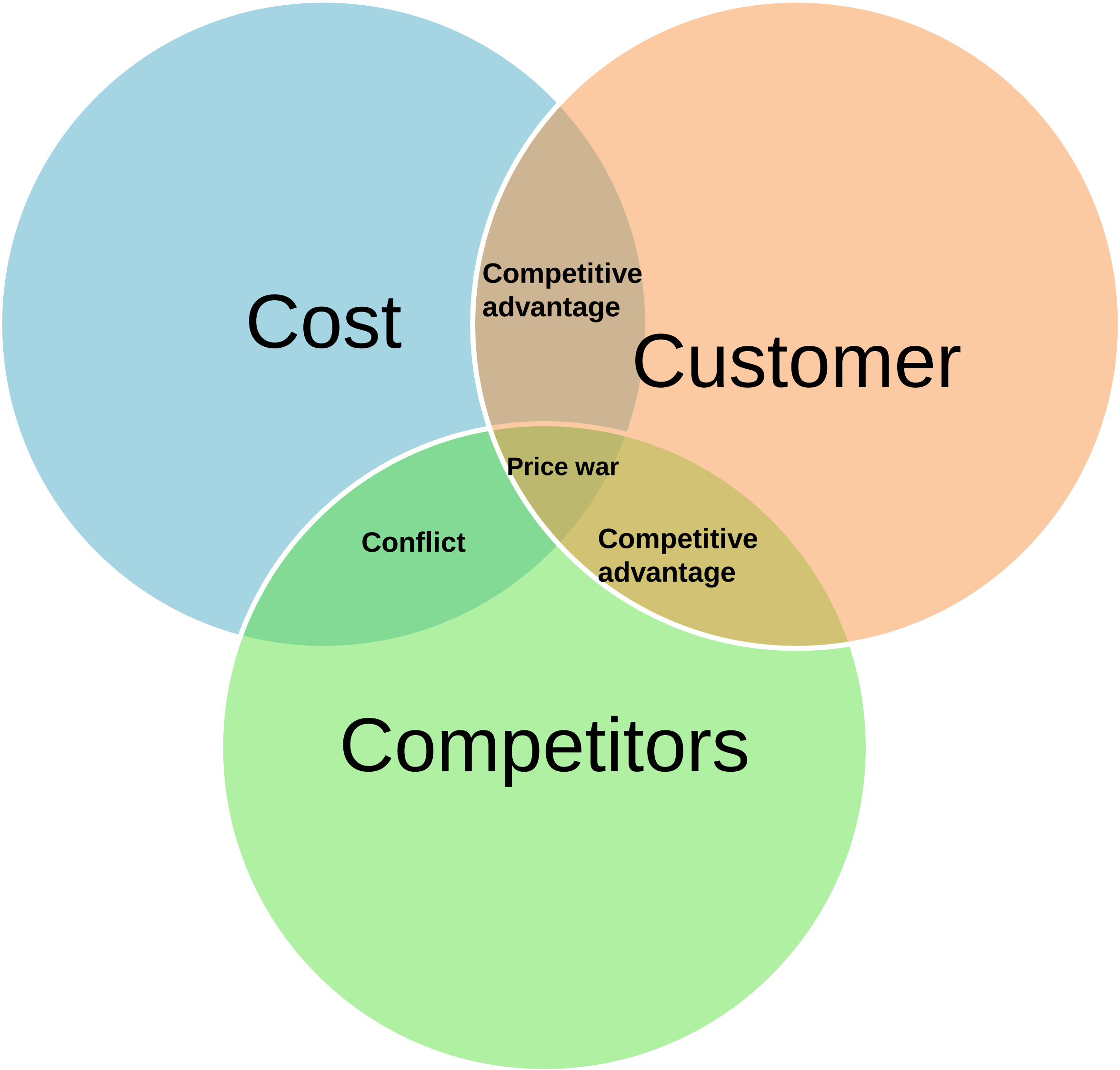
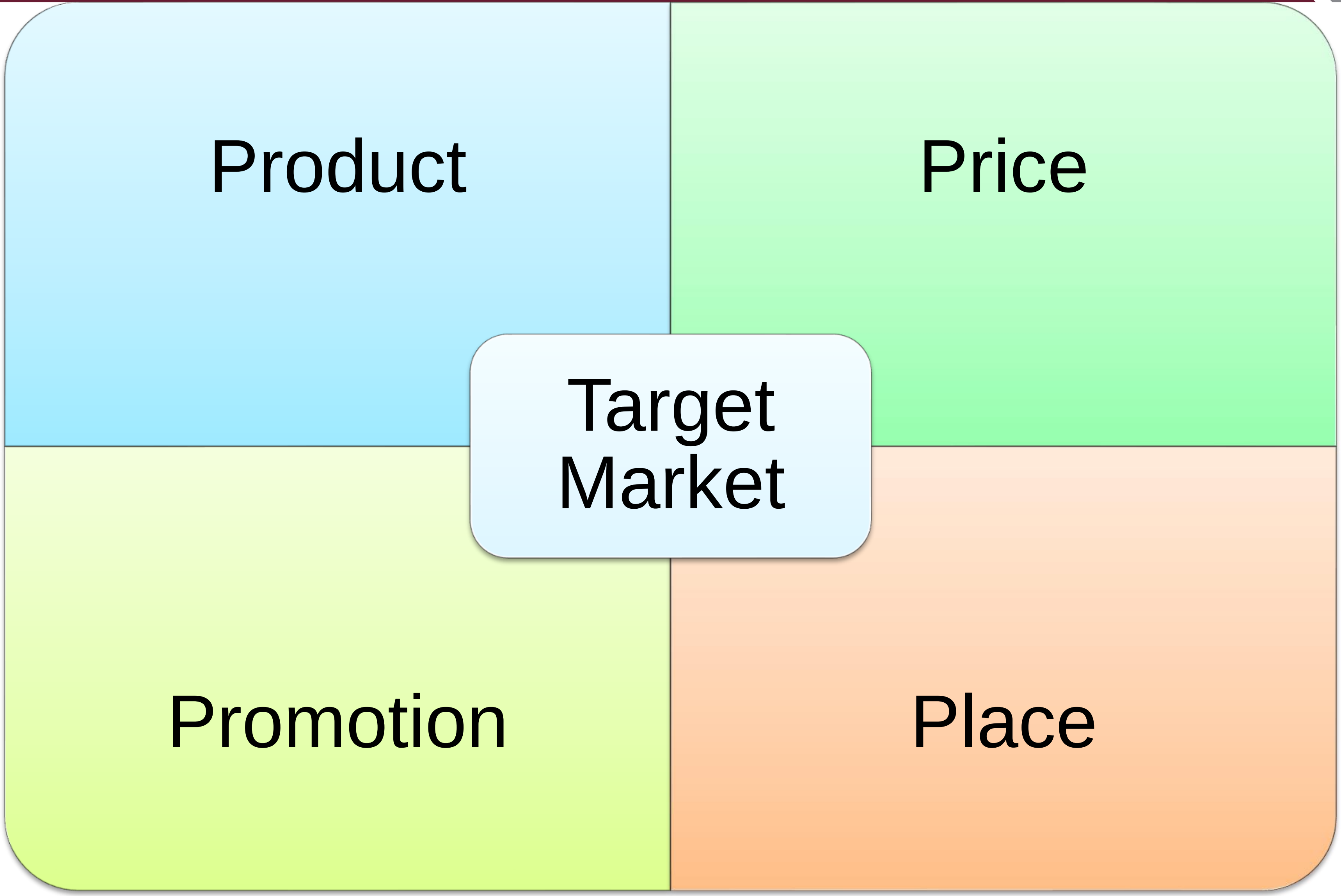
S Strength	W Weakness	O Opportunities	T Threats
• Factors or characteristics within a farm operation	• Factors or characteristics within a farm operation	• Internal factors • External factors	• Internal factors • External factors

The 3 Cs of Marketing



The Marketing Mix (4 Ps): Implementation



Product (& Services): App for Healthy Corner Stores

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- Development of an AI enhanced app that can be easily accessed and operated by small food store owners, local farmers, producers, wholesalers, and distributors that would offer the option for cooperative purchasing and delivery from farmers, producers, wholesalers, and distributors to enhance services and outreach.
- Platform: iOS, Android, or Cross-Platform
- Key Features: user registration and profiles, product listings and search functionality, order management and tracking, delivery logistics, payment and invoicing, communication and feedback, analytics and reporting, push notifications, and integration with social media.

Conclusion

- AI is a game-changer in agriculture, offering solutions that enhance productivity, sustainability, and efficiency.

- As technology evolves, the integration of AI in farming promises to address many of the challenges faced by the agricultural sector today, leading to a more prosperous and sustainable future for farmers.

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