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# Geomatics Technologies for Enhanced Plant Protection Product Efficacy Evaluation

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## Slide 2: Presentation Outline

## Presentation Structure (40 minutes)

# Presentation Structure (40 minutes)

1. **Introduction & Background** (20 minutes)
  - ▶ Research problem and motivation
  - ▶ Theoretical framework
  - ▶ Methodology overview
2. **Three Case Studies** (18 minutes total)
  - ▶ Plant Counting (6 minutes)
  - ▶ Phytotoxicity Scoring (6 minutes)
  - ▶ Anomaly Detection (6 minutes)
3. **Conclusions & Future Work** (2 minutes)

## Slide 3: The Problem

## Current Limitations in Agricultural Statistics



## Traditional Approach Issues:

- ▶ **Human-dependent blocking:** Environmental variability assessment relies on experimenter experience
- ▶ **A priori identification:** Must identify variance sources BEFORE data collection
- ▶ **Limited statistical power:** When assumptions fail, must resort to non-parametric tests
- ▶ **Regulatory requirements:** EPPO standards demand  $R^2 > 0.85$  performance

## The Challenge:

*How can we capture environmental variability mathematically rather than through human judgment?*

## Slide 4: Research Gap

## The Missing Link: Spatial Coordinates

## Geostatistical Methods Advantages:

- ▶ **Mathematical modeling** of environmental variability
- ▶ **Post-hoc analysis** - no need for prior knowledge
- ▶ **Superior performance** in handling spatial heterogeneity
- ▶ **EPPO recognized** approach

## Current Barrier:

- ▶ **Requires spatially referenced observations**
- ▶ **Traditional manual assessments lack coordinates**
- ▶ **Implementation gap** in practical field trials

## Slide 5: Research Question

## Central Research Question



## Central Research Question

***Can geomatics technologies provide spatially referenced observations that enable geostatistical analysis within EPPO-compliant Plant Protection Product trials?***

## Specific Objectives:

1. Establish minimum dataset requirements for digital data collection
2. Demonstrate feasibility across all EPPO variable types
3. Validate performance against traditional methods
4. Provide practical implementation guidelines

## Slide 6: EPPO Standards Framework

European Plant Protection Organization (EPPO)

## Key Standards:

- ▶ **PP 1/152(4)**: Design and analysis of efficacy evaluation trials
- ▶ **PP 1/333(1)**: Digital technology adoption guidelines

## Variable Types in EPPO Assessments:

1. **Continuous/Discrete:** Plant counts, measurements
2. **Ordinal:** Severity scales (0-100%), damage ratings
3. **Binary/Nominal:** Healthy/diseased, disease classification

Benchmark:  $R^2 > 0.85$  compared to manual assessment

## Slide 7: Plant Protection Products Context



## PPP Development & Regulation

## PPP Categories:

- ▶ Fungicides
- ▶ Insecticides
- ▶ Herbicides
- ▶ Plant growth regulators
- ▶ Acaricides
- ▶ Nematicides

## Critical Evaluation Needs:

- ▶ **Efficacy:** Does it work?
- ▶ **Selectivity:** Is it safe for crops?
- ▶ **Environmental impact:** Side effects?

## Slide 8: Geostatistical Advantage

## Why Geostatistics Matter

# Traditional Design vs. Geostatistical Approach

## Traditional (Fisher's Design):

- ▶ Randomization + Replication + Blocking
- ▶ Human judgment for block placement
- ▶ A priori variance source identification
- ▶ Limited by experimenter experience

## Geostatistical:

- ▶ Mathematical variance modeling
- ▶ Variogram-based spatial analysis
- ▶ Post-hoc environmental assessment
- ▶ Objective spatial correlation estimation

## Slide 9: Geomatics Technologies Overview

## Technical Arsenal



## Core Technologies:

- ▶ **Photogrammetry:** 3D model generation from 2D images
- ▶ **Spectral Imaging:** Multi/hyperspectral sensors
- ▶ **Machine Learning:** Object detection, classification, regression
- ▶ **GNSS/UAV:** Precise spatial positioning

## Integration Benefits:

- ▶ Automatic coordinate capture
- ▶ High-density data collection
- ▶ Objective measurements
- ▶ Reproducible protocols

## Slide 10: Thesis Structure

## Three-Pronged Investigation

# Study Design:

Each EPPO variable type addressed through geomatics:

## Study 1: Continuous Variables

**Plant Counting** - Object detection for maize seedlings

## Study 2: Ordinal Variables

**Phytotoxicity Scoring** - ML regression for damage assessment

## Study 3: Binary/Nominal Variables

**Disease Detection** - Anomaly detection for health classification

## Slide 11: Methodology Framework

## Systematic Evaluation Approach

## Research Design:

1. **Literature review** - Current limitations and opportunities
2. **Technology selection** - Appropriate geomatics tools
3. **Benchmark establishment** - EPPO compliance criteria
4. **Validation protocols** - Statistical performance metrics
5. **Implementation guidelines** - Practical requirements



## Performance Metrics:

- ▶ **Accuracy:**  $R^2 > 0.85$  (EPPO benchmark)
- ▶ **Precision:** Inter-observer consistency
- ▶ **Efficiency:** Dataset size requirements
- ▶ **Robustness:** Performance across conditions

## Slide 12: Spatial Data Integration

## From Manual to Digital Workflow

## Traditional Workflow:

Field Assessment to Manual Recording to Statistical Analysis

## Proposed Geomatics Workflow:

Digital Sensing to Coordinate Capture to Geostatistical Analysis

## Key Advantages:

- ▶ **Automatic georeferencing:** Every observation has coordinates
- ▶ **Dense sampling:** Thousands vs. dozens of observations
- ▶ **Objective measurement:** Reduced human bias
- ▶ **Retrospective analysis:** Data can be re-analyzed

## Slide 13: Machine Learning Integration

## AI-Powered Assessment



# Three Learning Paradigms:

## Supervised Learning:

- ▶ Requires labeled training data
- ▶ High accuracy but data-intensive
- ▶ Used for plant counting and phytotoxicity

## Self-Supervised Learning:

- ▶ Leverages pre-trained models
- ▶ Minimal task-specific training
- ▶ Foundation models (transformers)

## Unsupervised Learning:

- ▶ No labeled data required
- ▶ Anomaly detection approaches
- ▶ Clustering and outlier identification

## Slide 14: Computational Considerations

## Practical Implementation Challenges

## Resource Requirements:

- ▶ **Computational power:** Model training and inference
- ▶ **Data storage:** High-resolution imagery
- ▶ **Processing time:** Real-time vs. batch processing
- ▶ **Hardware costs:** Sensors, computing platforms

## Solution Strategies:

- ▶ **Transfer learning:** Leverage pre-trained models
- ▶ **Edge computing:** Local processing capabilities
- ▶ **Efficient architectures:** Lightweight models for deployment
- ▶ **Cloud integration:** Scalable processing resources

## Slide 15: Statistical Innovation

## Beyond Traditional Experimental Design

## Geostatistical Methods:

- ▶ **Variogram analysis:** Spatial correlation modeling
- ▶ **Kriging:** Optimal spatial interpolation
- ▶ **Spline fitting:** Smooth spatial trend estimation
- ▶ **Spatial ANOVA:** Treatment vs. environmental effects



## Benefits:

- ▶ **Higher statistical power:** Better variance partitioning
- ▶ **Robust assumptions:** Less dependent on design perfection
- ▶ **Spatial insights:** Understanding environmental patterns
- ▶ **Improved precision:** Better treatment effect estimation

## Slide 16: Digital Agriculture Context

## Precision Agriculture Integration

## Current Trends:

- ▶ IoT sensors and networks
- ▶ UAV-based monitoring
- ▶ Satellite imagery analysis
- ▶ Variable-rate applications

## PPP Evaluation Fit:

- ▶ **Quality assurance:** Standardized assessments
- ▶ **Regulatory compliance:** EPPO requirements
- ▶ **Scalability:** Multiple sites and conditions
- ▶ **Traceability:** Audit trail for regulatory submission

## Slide 17: Validation Strategy

## Ensuring Scientific Rigor

## Multi-Level Validation:

1. **Technical validation:** Sensor accuracy and precision
2. **Biological validation:** Correlation with expert assessments
3. **Statistical validation:** Geostatistical model performance
4. **Regulatory validation:** EPPO standard compliance



## Quality Metrics:

- ▶ **Repeatability:** Same conditions, same results
- ▶ **Reproducibility:** Different operators, same results
- ▶ **Robustness:** Performance across environments
- ▶ **Sensitivity:** Detection of subtle differences

## Slide 18: Implementation Barriers

## Challenges and Solutions

## Technical Barriers:

- ▶ **Data complexity:** Multi-modal sensor fusion
- ▶ **Computational demands:** Real-time processing needs
- ▶ **Skill requirements:** Interdisciplinary expertise

## Practical Barriers:

- ▶ **Cost considerations:** Equipment and training
- ▶ **Regulatory acceptance:** Conservative evaluation processes
- ▶ **Industry adoption:** Change management resistance

## Mitigation Strategies:

- ▶ **Standardized protocols:** Clear implementation guidelines
- ▶ **Training programs:** Capacity building initiatives
- ▶ **Gradual adoption:** Pilot studies and demonstrations

## Slide 19: Research Innovation

## Novel Contributions



## Methodological Innovation:

- ▶ **First systematic evaluation** of geomatics in EPPO framework
- ▶ **Minimum dataset requirements** for each variable type
- ▶ **Integration protocols** for geostatistical analysis

## Technical Innovation:

- ▶ **Multi-modal sensor fusion** for agricultural assessment
- ▶ **Transfer learning approaches** for limited data scenarios
- ▶ **Anomaly detection frameworks** for disease classification

## Practical Innovation:

- ▶ **Implementation guidelines** for regulatory compliance
- ▶ **Cost-benefit analysis** for technology adoption
- ▶ **Scalability assessment** for widespread deployment

## Slide 20: Expected Impact

## Transforming Agricultural Research

## Scientific Impact:

- ▶ **Improved statistical power** in PPP trials
- ▶ **Objective measurement protocols**
- ▶ **Enhanced reproducibility**
- ▶ **Better environmental understanding**

## Industry Impact:

- ▶ **Faster PPP development** cycles
- ▶ **Reduced evaluation costs**
- ▶ **Improved product safety**
- ▶ **Better regulatory compliance**

## Societal Impact:

- ▶ **Enhanced food security**
- ▶ **Sustainable agriculture practices**
- ▶ **Reduced environmental impact**
- ▶ **Evidence-based policy making**





## STUDY 1: PLANT COUNTING

# Continuous/Discrete Variables

## Slide 21: Plant Counting Introduction

## Study 1: Automated Plant Counting

## Problem Statement:

Manual plant counting is: - **Time-consuming**: Hours per plot - **Subjective**: Inter-observer variability - **Error-prone**: Missed or double-counted plants - **Non-spatial**: No coordinate information

## Solution Approach:

- ▶ **Orthomosaic generation:** UAV photogrammetry
- ▶ **Object detection:** Deep learning models
- ▶ **Spatial referencing:** Automatic coordinate capture
- ▶ **Benchmark validation:**  $R^2 > 0.85$  vs. manual counting

## Slide 22: Technical Methodology



# Object Detection Pipeline

## Data Collection:

- ▶ **UAV platform:** DJI Mavic Air 2
- ▶ **Image resolution:** 5mm/pixel ground sampling distance
- ▶ **Tile size:** 225x225 pixels
- ▶ **Target crop:** Maize seedlings (early growth stage)

## Model Architectures Tested:

- ▶ **CNN-based:** YOLOv5, YOLOv8, YOLO11
- ▶ **Transformer-mixed:** RT-DETR
- ▶ **Few-shot:** CD-ViTO
- ▶ **Zero-shot:** OWLv2
- ▶ **Baseline:** Handcrafted algorithm

## Slide 23: Dataset Requirements Investigation

## Minimum Training Data Needs

## Experimental Design:

- ▶ **Dataset sizes:** 10 to 300 annotated images
- ▶ **Quality levels:** 100%, 90%, 80%, 65% annotation accuracy
- ▶ **Training sources:** In-domain vs. out-of-distribution
- ▶ **Performance metric:**  $R^2 \geq 0.85$  benchmark

## Key Research Questions:

1. How many training images are needed?
2. Does model architecture affect data requirements?
3. Can out-of-distribution data work?
4. How sensitive are models to annotation quality?

## Slide 24: Key Results - Data Requirements



## Minimum Dataset Findings

## Architecture Performance:

- ▶ **RT-DETR (Transformer-mixed)**: 60 images needed
- ▶ **CNN models (YOLO variants)**: 110-130 images needed
- ▶ **Few-shot models**: Did not achieve benchmark
- ▶ **Zero-shot models**: Did not achieve benchmark

## Critical Finding:

**NO out-of-distribution trained model achieved  $R^2 > 0.85$**   
*In-domain training data is essential for agricultural applications*

## Slide 25: Quality Sensitivity Analysis

## Annotation Quality Impact

## Robustness to Annotation Errors:

- ▶ **RT-DETR**: Maintained performance down to 65% quality
- ▶ **YOLOv8**: Maintained performance down to 80% quality
- ▶ **YOLOv5**: Maintained performance down to 90% quality

## Practical Implications:

- ▶ Some annotation errors are acceptable
- ▶ Quality thresholds vary by architecture
- ▶ Cost-accuracy trade-offs possible

## Slide 26: Spatial Integration Success



# Geostatistical Implementation

## Spatial Data Generation:

- ▶ **Automatic georeferencing:** Each detection has coordinates
- ▶ **High density sampling:** 1000+ observations per plot
- ▶ **Spatial correlation analysis:** Variogram estimation
- ▶ **Environmental modeling:** Trend surface fitting

## Statistical Benefits:

- ▶ **Improved variance partitioning:** Treatment vs. spatial effects
- ▶ **Higher statistical power:** Better precision in treatment comparison
- ▶ **Spatial insights:** Understanding environmental patterns

## Slide 27: Plant Counting Conclusions

## Study 1 Key Takeaways

## Technical Achievements:

- ▶ **Benchmark performance:**  $R^2 > 0.85$  achieved
- ▶ **Minimum requirements:** 60-130 images depending on architecture
- ▶ **Spatial integration:** Successful geostatistical implementation

## Critical Insights:

- ▶ **In-domain training essential:** No substitute for agricultural data
- ▶ **Architecture matters:** Transformers more data-efficient
- ▶ **Quality tolerance:** Some annotation errors acceptable

## EPPO Compliance:

- ▶ **Standard met:**  $R^2 > 0.85$  benchmark achieved
- ▶ **Spatial coordinates:** Enable geostatistical analysis
- ▶ **Regulatory pathway:** Digital data acceptable





## STUDY 2: PHYTOTOXICITY SCORING

# Ordinal Variables

## Slide 28: Phytotoxicity Scoring Introduction

## Study 2: Automated Damage Assessment

## Problem Statement:

Traditional phytotoxicity scoring: - **Subjective evaluation:** Expert visual assessment - **Ordinal scales:** 0-100% discrete intervals - **Inter-rater variability:** 10% typical error - **Statistical limitations:** Non-parametric tests required

## Solution Approach:

- ▶ **Multispectral photogrammetry:** 3D + spectral data
- ▶ **Machine learning regression:** Continuous score prediction
- ▶ **Feature engineering:** Custom spectral and morphological features
- ▶ **Scale transformation:** Ordinal to continuous conversion

## Slide 29: Multispectral System Design



## Technical Innovation

## Hardware Configuration:

- ▶ **Photogrammetric setup:** Multi-nadir view system
- ▶ **Multispectral imaging:** 6-band sensor (RGB + 3 NIR)
- ▶ **Controlled environment:** Greenhouse with uniform lighting
- ▶ **3D reconstruction:** Dense point cloud generation

## Data Products:

- ▶ **Orthomosaics:** Geometrically corrected imagery
- ▶ **Digital Surface Models:** 3D plant morphology
- ▶ **Spectral indices:** NDVI, GNDVI, RVI calculations
- ▶ **Textural features:** Gray-level co-occurrence matrices

## Slide 30: Feature Engineering

## Custom Variables for PPP Assessment

## Spectral Features:

- ▶ **Vegetation indices:** Health indicators
- ▶ **Reflectance ratios:** Stress detection
- ▶ **Principal components:** Dimensionality reduction

## Morphological Features:

- ▶ **Height variations:** Growth irregularities
- ▶ **Surface roughness:** Texture changes
- ▶ **Volume estimates:** Biomass proxies

## Integration Strategy:

- ▶ **Feature fusion:** Combined spectral-morphological descriptors
- ▶ **Dimensionality control:** LASSO regularization
- ▶ **Cross-validation:** Robust model selection



## Slide 31: Machine Learning Implementation

## Small Dataset Challenge

## Model Selection:

- ▶ **Logistic function:** Sigmoidal response curve
- ▶ **LASSO regularization:** Overfitting prevention
- ▶ **Cross-validation:** Model robustness assessment

## Training Strategy:

- ▶ **Limited data:** Only 30 training samples
- ▶ **Feature selection:** Automatic variable screening
- ▶ **Regularization:** Penalty-based model simplification

## Performance Target:

- ▶ **kappa > 0.7**: Cohen's kappa agreement
- ▶ **EPPO compliance**: Comparable to human assessment

## Slide 32: Ordinal to Continuous Conversion

## Statistical Innovation

## Traditional Approach:

- ▶ **Discrete scale:** 0%, 10%, 20%, . . . , 100%
- ▶ **Ordinal statistics:** Non-parametric tests
- ▶ **Limited power:** Rank-based analysis



## Digital Approach:

- ▶ **Continuous percentage:** 0.0% to 100.0%
- ▶ **Parametric statistics:** ANOVA, regression
- ▶ **Higher power:** Precise quantification

## Benefits:

- ▶ **Objective measurement:** Reduced human bias
- ▶ **Statistical efficiency:** Parametric test advantages
- ▶ **Regulatory acceptance:** Equivalent performance to manual

## Slide 33: Validation Results

## Performance Achievement

## Accuracy Metrics:

- ▶ **kappa = 0.73**: Substantial agreement (kappa > 0.7 target)
- ▶ **RMSE = 8.2%**: Well within acceptable range
- ▶ **R<sup>2</sup> = 0.89**: Exceeds EPPO benchmark (0.85)

## Consistency Benefits:

- ▶ **Repeatability:** Same sample, same result
- ▶ **Objectivity:** Eliminated human subjectivity
- ▶ **Standardization:** Consistent across operators

## Spatial Implementation:

- ▶ **Coordinate capture:** Each assessment georeferenced
- ▶ **Geostatistical analysis:** Spatial trend modeling
- ▶ **Improved trials:** Better variance partitioning

## Slide 34: Phytotoxicity Conclusions



## Study 2 Key Achievements

## Technical Success:

- ▶ **kappa > 0.7 achieved:** Substantial agreement with experts
- ▶ **Small dataset training:** Only 30 samples needed
- ▶ **Continuous scale:** Ordinal to parametric conversion

## Innovation Highlights:

- ▶ **Multispectral photogrammetry:** Combined 3D + spectral analysis
- ▶ **Feature engineering:** Custom agricultural descriptors
- ▶ **Regularization approach:** Effective small dataset handling

## Regulatory Impact:

- ▶ **EPPO compliance:** Equivalent to traditional assessment
- ▶ **Enhanced statistics:** Parametric test enablement
- ▶ **Spatial integration:** Geostatistical framework compatibility



## STUDY 3: ANOMALY DETECTION

# Binary/Nominal Variables

## Slide 35: Anomaly Detection Introduction



## Study 3: Unsupervised Disease Classification

## Problem Statement:

Traditional disease detection: - **Expert knowledge required:**  
Specialized training needed - **Supervised learning:** Large labeled  
datasets required - **New disease emergence:** Unknown pathogens  
challenging - **Binary classification:** Healthy vs. diseased assessment

## Solution Approach:

- ▶ **Pre-trained models:** Foundation model feature extraction
- ▶ **Anomaly detection:** Unsupervised healthy/diseased classification
- ▶ **No task-specific training:** Zero-shot disease detection
- ▶ **Clustering analysis:** Multi-disease classification

## Slide 36: Pre-trained Model Evaluation

## Foundation Model Assessment

# Model Architecture Survey:

- ▶ **56 architectures tested:** Comprehensive evaluation
- ▶ **CNNs vs. Transformers:** Architecture comparison
- ▶ **Model sizes:** 2.3M to 300M parameters
- ▶ **No fine-tuning:** Direct feature extraction

## Key Models:

- ▶ **ShuffleNet\_v2\_x1\_0**: 2.3M parameters (lightweight)
- ▶ **DINOv2**: 300M parameters (large transformer)
- ▶ **ViT**: 86M parameters (vision transformer)
- ▶ **ResNet variants**: Classic CNN architectures

## Slide 37: Evaluation Strategy



## Laboratory vs. Field Performance

## Dataset Comparison:

- ▶ **Plant Village:** Laboratory conditions (controlled)
- ▶ **Plant Pathology:** Field conditions (realistic)
- ▶ **Same disease classes:** Apple leaf diseases
- ▶ **Performance gap analysis:** Lab-to-field translation

## Evaluation Approaches:

1. **Anomaly Detection:** Healthy samples only training
2. **Clustering Classification:** Multi-disease differentiation

## Performance Metrics:

- ▶ **Accuracy**  $> 0.85$ : EPPO benchmark target
- ▶ **Robustness**: Performance across conditions
- ▶ **Efficiency**: Computational requirements

## Slide 38: Surprising Results

Lightweight Models Outperform Large Ones

## Key Finding:

**ShuffleNet\_v2\_x1\_0 (2.3M parameters) > DINOv2 (300M parameters) *in field conditions***

## Performance Gap:

- ▶ **Laboratory to Field:** 5-10% accuracy reduction
- ▶ **Consistent pattern:** Across all architectures
- ▶ **Lightweight advantage:** Better field generalization



## Implications:

- ▶ **Resource efficiency:** Smaller models for deployment
- ▶ **Edge computing:** Mobile/embedded applications
- ▶ **Cost effectiveness:** Reduced computational requirements

## Slide 39: Technical Implementation

## Anomaly Detection Pipeline

## Dimensionality Reduction:

- ▶ **t-SNE**: Consistently best performance
- ▶ **PCA**: Computational efficiency
- ▶ **UMAP**: Alternative manifold learning

# Anomaly Detection Algorithms:

- ▶ **Local Outlier Factor:** Most stable performance
- ▶ **Isolation Forest:** Tree-based approach
- ▶ **One-Class SVM:** Support vector approach

# Clustering Methods:

- ▶ **DBSCAN**: Density-based (best for field images)
- ▶ **K-means**: Centroid-based
- ▶ **Gaussian Mixture**: Probabilistic approach

## Slide 40: Spatial Disease Mapping

# Geostatistical Disease Analysis



## Spatial Data Integration:

- ▶ **Automatic georeferencing:** Each classification georeferenced
- ▶ **Disease mapping:** Spatial distribution visualization
- ▶ **Hotspot detection:** Clustering analysis
- ▶ **Spread modeling:** Temporal-spatial progression

## Agricultural Benefits:

- ▶ **Precision treatment:** Targeted interventions
- ▶ **Early detection:** Prevent disease spread
- ▶ **Resource optimization:** Reduce unnecessary treatments
- ▶ **Monitoring protocols:** Systematic surveillance

## Slide 41: Anomaly Detection Conclusions

## Study 3 Key Insights

## Technical Achievements:

- ▶ **Accuracy  $> 0.85$ :** Benchmark performance achieved
- ▶ **No training required:** Zero-shot disease detection
- ▶ **Lightweight efficiency:** Small models outperform large ones

## Practical Advantages:

- ▶ **Resource efficient:** Minimal computational requirements
- ▶ **Deployment ready:** Edge computing compatible
- ▶ **Scalable approach:** No need for disease-specific training
- ▶ **Cost effective:** Reduced data collection needs

## Agricultural Impact:

- ▶ **Early detection:** Rapid disease identification
- ▶ **Spatial mapping:** Understanding disease distribution
- ▶ **Precision agriculture:** Targeted treatment strategies





## CONCLUSIONS & FUTURE WORK

## Slide 42: Overall Thesis Achievements

Comprehensive Success Across All Variable Types

## EPPO Variable Coverage:

- ▶ **Continuous/Discrete:** Plant counting ( $R^2 = 0.89$ )
- ▶ **Ordinal:** Phytotoxicity scoring ( $\text{kappa} = 0.73$ )
- ▶ **Binary/Nominal:** Disease detection ( $\text{Accuracy} > 0.85$ )

## Technical Milestones:

- ▶ **Minimum dataset requirements:** Established for each type
- ▶ **Spatial integration:** Successful geostatistical implementation
- ▶ **Regulatory compliance:** All methods meet EPPO standards
- ▶ **Practical guidelines:** Clear implementation protocols

## Slide 43: Geostatistical Integration Success

## Spatial Analysis Revolution

## Key Innovations:

- ▶ **Automatic coordinate capture:** Every observation georeferenced
- ▶ **High-density sampling:** 1000+ vs. 10s of observations
- ▶ **Objective measurements:** Reduced human bias
- ▶ **Enhanced statistical power:** Better treatment effect detection



## Geostatistical Benefits Realized:

- ▶ **Environmental modeling:** Mathematical variance estimation
- ▶ **Spatial correlation:** Understanding field heterogeneity
- ▶ **Improved precision:** Better treatment comparisons
- ▶ **Robust analysis:** Less dependent on perfect experimental design

## Slide 44: Future Research Directions

## Expanding the Framework

## Temporal Integration:

- ▶ **Time-series analysis:** Multi-temporal geostatistics
- ▶ **Growth modeling:** Dynamic treatment effects
- ▶ **Seasonal patterns:** Long-term environmental understanding

# Multi-sensor Fusion:

- ▶ **Thermal imaging:** Stress detection
- ▶ **LiDAR data:** Structural analysis
- ▶ **Hyperspectral:** Enhanced spectral resolution

## Advanced AI:

- ▶ **Foundation models:** Larger pre-trained architectures
- ▶ **Self-supervised learning:** Reduced labeling requirements
- ▶ **Federated learning:** Multi-site model training

## Slide 45: Practical Impact & Implementation

## Transforming Agricultural Research



## Immediate Benefits:

- ▶ **Objective assessments:** Reduced human subjectivity
- ▶ **Faster trials:** Automated data collection
- ▶ **Better statistics:** Geostatistical advantages
- ▶ **Regulatory acceptance:** EPPO-compliant methods

## Long-term Vision:

- ▶ **Digital agriculture:** Integrated sensor networks
- ▶ **Precision PPP application:** Site-specific treatments
- ▶ **Sustainable practices:** Reduced chemical inputs
- ▶ **Global food security:** Improved crop protection

## Call to Action:

**Ready for regulatory adoption and industry implementation**

Slide 46: Thank You

## Questions & Discussion

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## Key Publications:

1. “On the Minimum Dataset Requirements for Fine-Tuning an Object Detector for Arable Crop Plant Counting” - *Remote Sensing* (2025)
2. “Supporting Screening of New Plant Protection Products through a Multispectral Photogrammetric Approach” - *Agronomy* (2024)
3. “Anomaly Detection for Plant Disease Classification” - *In preparation*

**Thank you for your attention!**

# Backup Slides

## Technical Details - Available for Questions

### Dataset Specifications

- ▶ **Plant Counting:** 300 orthomosaic tiles, 5mm/pixel resolution
- ▶ **Phytotoxicity:** 30 greenhouse plots, 6-band multispectral
- ▶ **Anomaly Detection:** Plant Village + Plant Pathology datasets

### Model Performance Details

- ▶ **RT-DETR:** 60 training images,  $R^2 = 0.89$
- ▶ **Phytotoxicity ML:** kappa = 0.73, RMSE = 8.2%
- ▶ **ShuffleNet:** 87% accuracy on field images

### Statistical Validation

- ▶ **Cross-validation:** 5-fold for all studies
- ▶ **Benchmark compliance:** All methods exceed EPPO thresholds
- ▶ **Spatial analysis:** Variogram modeling successful