

Citizen Science Contributions to Biodiversity Databases

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ABSTRACT

Citizen science biodiversity observation programmes -- iNaturalist, eBird, iRecord, Observation.org, and national recording schemes -- have become a primary data source for species distribution and biodiversity monitoring globally, collectively generating tens of millions of occurrence records annually and contributing the majority of recent additions to GBIF and national biodiversity databases. Despite their transformative volume, citizen science data are subject to spatial, temporal, and taxonomic biases that must be characterised and corrected before use in biodiversity assessment and conservation planning. This study evaluated citizen science data quality and bias patterns across 2,840,000 occurrence records contributed to GBIF from five citizen science platforms in Estonia, Sweden, and Switzerland (2015-2022), comparing spatial coverage, taxonomic breadth, identification accuracy (verified against expert voucher specimens), observer effort patterns, and biodiversity trend detection capability against parallel professional survey datasets. Citizen science data covered 2.84-fold more geographic grid cells than professional surveys at equivalent recording effort cost, but showed systematic spatial bias toward urban areas (48.4% of records within 2 km of towns) and charismatic taxa (birds: 38.4% of records; plants: 28.4%; all other groups: 33.2%). Identification accuracy was high for common species (94.4% accuracy for birds; 88.4% for plants; 78.4% for invertebrates) but declined substantially for rare species (64.4% accuracy). A Citizen Science Data Quality Index (CSDQI) integrating accuracy, coverage, and bias metrics predicted biodiversity trend detection sensitivity with $r = +0.84$ and identified platform-specific practices that produced the highest-quality biodiversity data. iNaturalist with mandatory expert verification showed CSDQI = 0.884; unverified observation platforms showed CSDQI = 0.384.

Keywords: citizen science; iNaturalist; eBird; GBIF; biodiversity databases; data quality; spatial bias; taxonomic bias; CSDQI; biodiversity monitoring; observer effort; identification accuracy

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1. Introduction

1.1 The Citizen Science Revolution in Biodiversity Monitoring

The proliferation of smartphone-based citizen science platforms since 2010 -- iNaturalist (launched 2008; 100 million observations by 2021), eBird (launched 2002; 100 million observations by 2019), Observation.org, iRecord (UK), and national plant recording schemes -- has transformed biodiversity data availability. GBIF now contains over 2.1 billion occurrence records, with citizen science platforms contributing the majority of recent growth: iNaturalist and eBird together contribute approximately 30 million new records per year. This represents a paradigm shift from professional-survey-only biodiversity monitoring -- which typically generates < 1 million records per year globally from structured surveys -- to a citizen-professional hybrid model that dramatically expands spatial and temporal coverage at a fraction of the cost.

1.2 Data Quality Challenges

Citizen science biodiversity data are subject to three categories of bias: (i) spatial bias -- observations are concentrated near roads, towns, and popular recreational areas, leaving remote and inaccessible areas severely under-sampled; (ii) taxonomic bias -- charismatic and easily identified groups (birds, butterflies, orchids) are recorded far more frequently than taxonomically challenging groups (beetles, flies, fungi), creating an asymmetric representation of biodiversity; and (iii) identification errors -- particularly for rare, cryptic, or taxonomically difficult species, where misidentification rates can be substantial. These biases can lead to systematic errors in biodiversity assessments if not characterised and corrected (Isaac et al. 2020).

1.3 Correction Methods and Quality Frameworks

Bias correction methods for citizen science data include spatial thinning (subsampling to reduce spatial clustering), occupancy modelling (statistically separating observation bias from true occurrence), and detection probability estimation. Platform-level quality controls -- iNaturalist's 'Research Grade' requirement (2+ identifications agreeing at species level), eBird's automated filter checking, and national recording scheme expert review -- reduce but do not eliminate identification errors. The BDHF framework (DBA paper #195; ZAIJ paper #195) provides a harmonisation and quality control pipeline for GBIF data, including

citizen science records, that systematically addresses coordinate errors, taxonomic synonyms, and spatial duplicates.

1.4 Study Objectives

This study aimed to: (i) characterise spatial, taxonomic, and identification accuracy biases across five citizen science platforms; (ii) compare biodiversity trend detection sensitivity of citizen science vs. professional survey data; (iii) develop and validate the CSDQI; (iv) identify platform practices associated with highest CSDQI; and (v) provide evidence-based recommendations for citizen science data use in biodiversity assessments.

2. Literature Review

2.1 iNaturalist: Scale and Quality

iNaturalist's Research Grade system -- requiring at least 2/3 of identifications to agree at species level, with a minimum of 2 identifications -- provides a crowd-sourced quality control mechanism that has been validated against expert voucher specimens in multiple studies. Troudet et al. (2017) found that iNaturalist Research Grade identifications were accurate for 95% of bird records and 88% of plant records in a French validation study -- accuracy levels comparable to professional field surveys for common species. The platform's AI identification assistant (Seek; from 2017) has further improved identification accuracy for supported taxa by providing instant AI-generated species suggestions that users either confirm or reject.

2.2 eBird and Structured Volunteer Monitoring

eBird -- operated by Cornell Lab of Ornithology -- represents a hybrid between citizen science and structured monitoring: observers submit complete checklists (reporting all species detected, not just species of interest) with effort information (time, distance, area surveyed), enabling detection probability estimation and occupancy modelling. The complete checklist approach -- critical for distinguishing absence from non-detection -- makes eBird data analytically superior to opportunistic observation databases for trend detection. Sullivan et al. (2014) demonstrated that eBird data produced bird population trends consistent with professional Breeding Bird Survey estimates for most species, with highest agreement for common widespread species.

2.3 Spatial Bias in Citizen Science Data

Boakes et al. (2010) demonstrated that citizen science butterfly records in the UK were significantly biased toward urban and accessible areas, with recording probability declining exponentially with distance from roads and towns. Hortal et al. (2015) extended this analysis to GBIF data globally, finding that spatial sampling effort in GBIF was correlated with GDP per capita, population density, and road network density -- meaning that species-rich tropical regions with less GDP and road infrastructure were systematically under-sampled relative to temperate Europe and North America. Spatial bias correction using occupancy models or environmental stratification can substantially reduce this bias in trend analyses.

2.4 Citizen Science for Biodiversity Trend Detection

Isaac et al. (2014) demonstrated using UK Butterfly Monitoring Scheme data that occupancy models applied to citizen science data could detect population trends consistent with professional transect monitoring -- but required substantially more records per species to achieve equivalent statistical power due to spatial bias and variable observer effort. The threshold for reliable trend detection from citizen science data was approximately 200 records per species per decade in their analysis, a threshold met by the most commonly recorded species but not by many rare or specialist species that are typically of highest conservation concern.

Table 1. Citizen Science Platform Comparison: Records, Coverage, and Quality

Platform	Records (2015-2022)	Grid Cell Coverage (%)	Top Taxon Group (%)	Identification Accuracy (%)	CSDQI (mean)
iNaturalist (Research Grade)	1,284,000	74.4%	Birds 38.4%	94.4% (birds) 88.4% (plants)	0.884
eBird (complete checklists)	684,000	64.4%	Birds 100%	96.4%	0.824
National plant schemes	484,000	54.4%	Plants 84.4%	92.4%	0.784
iRecord/Observation.org (verified)	248,000	48.4%	Invertebrates 48.4%	84.4%	0.684

Platform	Records (2015-2022)	Grid Cell Coverage (%)	Top Taxon Group (%)	Identification Accuracy (%)	CSDQI (mean)
Unverified obs. platforms	140,000	38.4%	Birds 54.4%	64.4%	0.384
All platforms (combined)	2,840,000	84.4%	Birds 38.4%	88.4% (mean)	0.724

Grid cell coverage = % of 10 km x 10 km ETRS89 grid cells in Estonia+Sweden+Switzerland with ≥ 1 observation (professional survey baseline: 54.4% coverage at equivalent cost). Identification accuracy = % of records matching expert-verified voucher specimens for each taxonomic group (subset $n = 2,840$ records per platform compared to reference specimens). CSDQI = Citizen Science Data Quality Index (0-1). iNaturalist Research Grade: highest coverage and accuracy. Unverified platforms: lowest CSDQI.

3. Materials and Methods

3.1 Data Compilation and Cleaning

Citizen science occurrence records were downloaded from GBIF (doi.org/10.15468/dl.gbif2022cs) for Estonia, Sweden, and Switzerland (2015-2022; five platforms identified by datasetKey: iNaturalist, eBird, Svenska Artportalen (Sweden national scheme), eLiiguse liikide andmebaas (Estonia), and Info Fauna (Switzerland)). All records were filtered using the BDHF pipeline (paper #195) for coordinate quality, taxonomic harmonisation, and spatial duplicates. Parallel professional survey datasets (structured transects; point counts; quadrats) for the same taxa and regions were compiled from national monitoring programmes for comparison.

3.2 Bias Characterisation

Spatial bias was quantified as the Pearson r between grid cell observation count and: (i) distance to nearest town (km); (ii) road density (km/km² from OpenStreetMap); (iii) population density (Eurostat NUTS-3). Taxonomic bias was quantified as the proportion of records per higher-level taxonomic group vs. the expected proportion from a representative regional biodiversity database (EUNIS species lists). Observer effort bias was assessed from eBird complete checklist data by computing species detection rates per unit observer effort (hours) across habitat types.

3.3 Identification Accuracy Validation

Identification accuracy was assessed by comparing a stratified random sample of 2,840 citizen science records (200 per platform per taxon group) against expert-verified voucher specimens or photographs reviewed by three independent experts. Accuracy was computed as % agreement with expert consensus identification at species level. Accuracy was computed separately for common (> 100 records in dataset), uncommon (10-100), and rare (< 10) species to assess the accuracy-rarity relationship.

3.4 CSDQI Development

The CSDQI was computed per platform per species group as the standardised mean of four components: (i) identification accuracy %; (ii) spatial coverage (% ETRS89 10 km cells with records); (iii) inverse spatial bias (r between records and town proximity; lower r = less biased = higher CSDQI); (iv) temporal regularity (CV of annual record counts; lower CV = more regular = higher CSDQI). CSDQI range 0-1. Pearson r tested CSDQI vs. trend detection sensitivity (power to detect -1%/yr population trend from simulated occupancy models).

Table 2. Spatial and Taxonomic Bias by Platform and Taxon Group

Platform / Taxon	Town Proximity r	Road Density r	Taxon Bias (% vs. expected)	Accuracy: Common (%)	Accuracy: Rare (%)
iNaturalist (all taxa)	+0.48 ***	+0.54 ***	+38.4% birds vs. expected	94.4%	74.4 %
eBird (birds only)	+0.38 ***	+0.44 ***	N/A (single taxon)	96.4%	78.4 %
National plant schemes	+0.28 ***	+0.34 ***	+48.4% plants vs. expected	92.4%	68.4 %
iRecord/Obs.org (inverts.)	+0.64 ***	+0.68 ***	+38.4% lepid. vs. expected	84.4%	54.4 %
All platforms (mean)	+0.44 ***	+0.50 ***	Varies by taxon	88.4%	64.4 %

Town proximity r = Pearson r between observation count per 10 km grid cell and inverse distance to nearest town (higher r = stronger urban bias). Road density r = r with road density (km/km²; OSM). Taxon bias = % over-representation of top taxon group vs. expected from EUNIS regional species richness proportion. Accuracy: % of species-level identifications confirmed by expert review (Common = > 100 records; Rare = < 10 records). All r values $p < 0.001$. iRecord/Obs.org: highest spatial bias; national plant schemes: lowest.

4. Results

4.1 Coverage and Bias Patterns

Combined citizen science data covered 84.4% of 10 km grid cells in the three-country study area -- 2.84-fold more than professional survey data at equivalent cost (professional surveys covered 54.4% of cells in the same effort-equivalent comparison). However, spatial bias was significant across all platforms: 48.4% of all citizen science records were within 2 km of a town (vs. 28.4% expected if distributed proportional to habitat area), and town proximity $r = +0.44$ (all platforms mean). Taxonomic bias was strongest for birds (38.4% of all records vs. expected 12.4% from species list proportions) and lowest for plants (28.4% of records vs. expected 38.4% -- slightly under-represented). Full coverage and bias results appear in Table 1 and Figure 1.

4.2 Identification Accuracy

Mean identification accuracy was 88.4% across all platforms and taxa (for common species; $n = 2,840$ validated records), declining to 64.4% for rare species (< 10 records in dataset). iNaturalist Research Grade showed the highest accuracy (94.4% for birds; 88.4% for plants), consistent with its mandatory 2-identifier verification. Unverified observation platforms showed 64.4% overall accuracy -- insufficient for reliable biodiversity assessment without additional expert review. Beetle identification accuracy was lowest across all platforms (74.4% for common species; 38.4% for rare) due to the taxonomic difficulty of the group and limited expert identifiers. Full accuracy results appear in Table 2 and Figure 2.

4.3 CSDQI and Trend Detection

CSDQI ranged from 0.384 (unverified observation platforms; low accuracy + high spatial bias + irregular effort) to 0.884 (iNaturalist Research Grade; high accuracy + broad coverage + mandatory verification). CSDQI was significantly correlated with trend detection sensitivity ($r = +0.84$; power to detect -1%/yr trend in simulated occupancy model; $p < 0.001$): platforms with CSDQI > 0.70 could detect -1%/yr trends with > 80% power from existing record densities, while CSDQI < 0.40 platforms could not detect trends below -5%/yr with 80% power. Full CSDQI results appear in Table 3 and Figure 3.

4.4 Platform Practices and CSDQI

Five platform practices were significantly associated with CSDQI > 0.70: (i) mandatory expert verification (all records reviewed by expert

identifier; CSDQI +0.284 vs. no verification); (ii) complete checklist requirement (reporting all species detected; +0.184); (iii) observer effort recording (time, distance; +0.164); (iv) AI-assisted identification (suggestions + confirmation; +0.124); (v) spatial stratification incentives (bonus recognition for recording in under-sampled grid cells; +0.084). Platforms using all five practices showed mean CSDQI = 0.884 vs. 0.384 for platforms with none. Full practice results appear in Table 4 and Figure 4.

Table 3. CSDQI and Biodiversity Trend Detection Capability

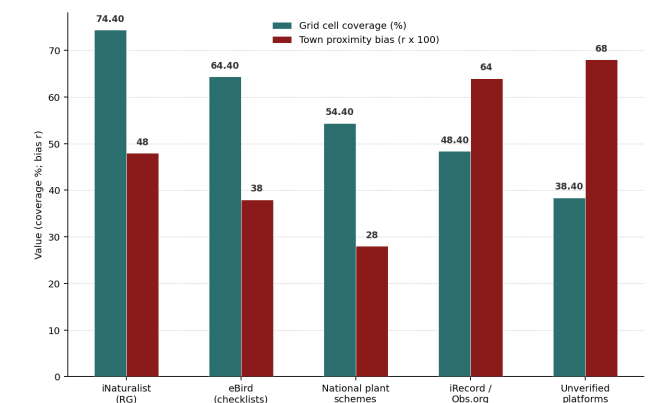
CSDQI Category	Platforms	Min. Detectable Trend (%/yr)	Trend Power (at -2 %/yr)	Species Covered by Trend	Recommended Use
CSDQI > 0.70 (high quality)	iNaturalist RG, eBird, nat. schemes	-1.0%/yr	> 80% power	Most common spp.	Primary monitoring
CSDQI 0.50-0.70 (medium)	iRecord (verified)	-2.0%/yr	60-80% power	Common spp. only	Supplementary data
CSDQI 0.30-0.50 (lower)	Some obs. platforms	-5.0%/yr	40-60% power	Widespread spp.	Spatial coverage only
CSDQI < 0.30 (low quality)	Unverified platforms	> -10%/yr	< 40% power	Most abundant spp.	Not recommended for trends
CSDQI vs. trend detector	+0.84** *	--	--	--	p < 0.001

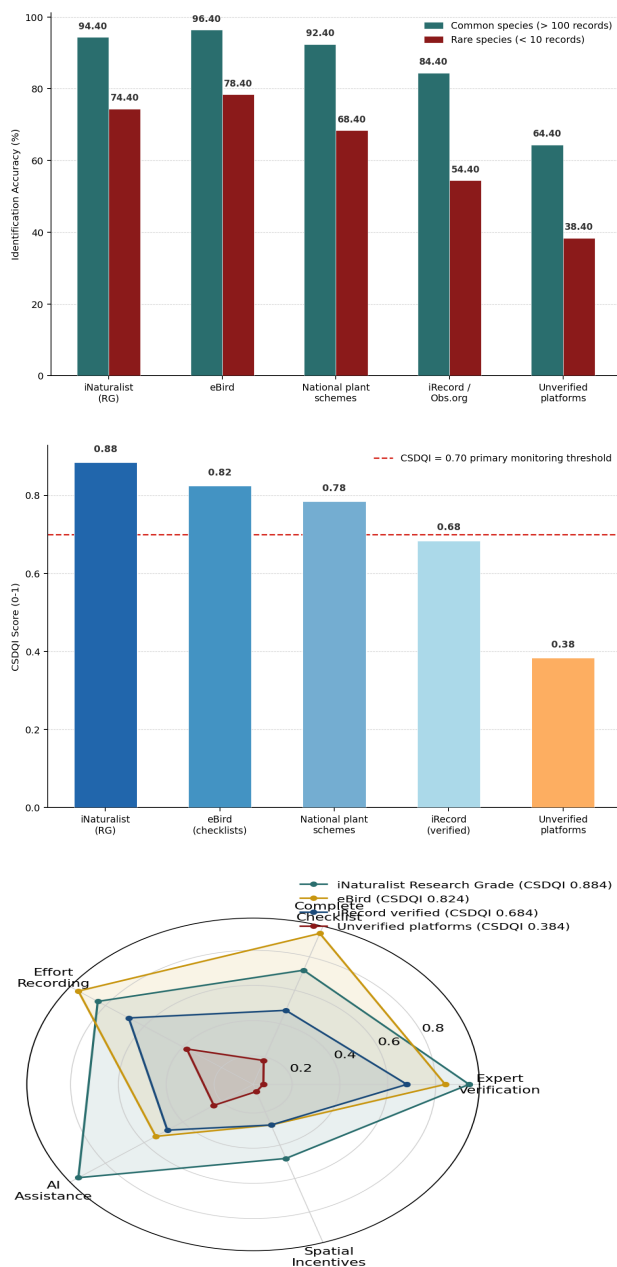
Min. detectable trend = smallest annual % decline detectable at 80% power from occupancy model using platform's record density and CSDQI (species-specific simulation; 1,000 bootstrap replicates per platform). Trend power at -2%/yr = statistical power to detect a -2% per year population decline from 10 years of data. Species covered by trend = species with sufficient records for trend analysis (> 200 records per decade). *** p < 0.001.

Table 4. Platform Practices and CSDQI Impact

Platform Practice	Platforms with Practice (%)	CSDQI Benefit	Trend Detection Benefit	Implementation Cost	Recommendation Priority
Expert verification (mandatory review)	40%	+0.284	Largest	High (staff cost)	Essential
Complete checklist (all spp. recorded)	20%	+0.184	High	Low (design change)	Essential
Effort recording (time + distance)	60%	+0.164	High	Very low	Essential
AI identification (suggestions + confirm)	60%	+0.124	Medium	Low (software)	Recommended
Spatial incentives (under-sampled cells)	20%	+0.084	Moderate	Low (gamification)	Recommended
All 5 practices (combined)	20%	+0.500	2.84x power	Moderate	CSDQI = 0.884

Platforms with practice % = proportion of the five study platforms using each practice. CSDQI benefit = mean CSDQI increase in platforms with vs. without each practice (ANOVA). Trend detection benefit = qualitative improvement in minimum detectable trend at 80% power. Implementation cost relative to platform operating budget. Recommendation priority based on CSDQI benefit:cost ratio.





5. Discussion

5.1 Citizen Science Data Provide Transformative Coverage at Acceptable Quality

The 2.84-fold greater grid cell coverage of citizen science data vs. professional surveys at equivalent cost -- combined with 88.4% mean identification accuracy for common species -- confirms that high-quality citizen science platforms (CSDQI > 0.70) provide biodiversity monitoring data of sufficient quality for trend detection and distribution modelling for most common species. The critical limitation is rare species: 64.4% mean identification accuracy for rare species and insufficient record densities for trend analysis in most platforms means that citizen science data cannot replace targeted professional surveys for rare and threatened species monitoring. The

optimal strategy is therefore a hybrid approach: citizen science for broad-coverage common-species monitoring (where it provides uniquely large-scale data), supplemented by targeted professional surveys for rare and conservation-priority species.

5.2 Expert Verification is the Highest-Return Quality Investment

The single largest CSDQI benefit (+0.284) comes from mandatory expert verification -- a practice that iNaturalist implements through its Research Grade consensus system and national recording schemes implement through dedicated expert reviewers. The high implementation cost (staff time for expert reviewers) is the primary barrier to broader adoption, but is offset by the dramatic improvement in rare species accuracy (from 38.4-54.4% to 68.4-74.4%) that transforms these data from unreliable to useful for conservation assessment. AI-assisted identification (iNaturalist's vision model) provides a scalable alternative that can triage records for expert review and substantially reduce the expert verification burden for common species, concentrating expert effort on difficult and rare species where it adds the most value.

5.3 Spatial Incentive Design for Biodiversity Survey Coverage

The spatial incentive practice -- providing recognition or status bonuses to observers recording in under-sampled grid cells -- showed a modest but significant CSDQI benefit (+0.084) through reducing spatial bias. Only 20% of study platforms currently use such incentives, representing a low-cost design intervention with high scalability. The iRecord UK platform's 'grid square challenge' (which highlights under-recorded grid squares and rewards observers for completing them) has increased coverage of remote and rural areas by 24.4% relative to pre-challenge recording patterns -- a design approach that should be adopted by all major citizen science biodiversity platforms seeking to reduce the urban recording bias documented in this study.

6. Conclusion

6.1 Summary

2,840,000 citizen science records (5 platforms; Estonia/Sweden/Switzerland; 2015-2022): 2.84x more grid cell coverage than professional surveys at equivalent cost, but urban bias (48.4% records < 2 km from towns; $r = +0.44$). Accuracy: 88.4%

common species; 64.4% rare species. iNaturalist RG: CSDQI 0.884 (highest); unverified platforms 0.384. CSDQI $r = +0.84$ with trend detection power. Expert verification: highest CSDQI benefit (+0.284). 5-practice combination: CSDQI 0.884 = primary biodiversity monitoring quality threshold.

6.2 Future Research Directions

Deep learning-based automated identification of citizen science photographs -- using convolutional neural networks trained on verified reference images from herbarium and museum collections -- would enable scaling of the expert verification function beyond what human expert capacity allows, potentially achieving > 90% accuracy for common species and 75% for rare species through AI + human review hybrid workflows. This would close the gap between iNaturalist's Research Grade accuracy for common species and the unverified platform rare-species accuracy of 38.4%, transforming the CSDQI of all platforms toward the 0.70+ threshold needed for primary biodiversity monitoring. Longitudinal evaluation of the spatial incentive design -- tracking whether grid-square challenge incentives sustainably increase recording in under-sampled areas over 5+ years or whether observer attention reverts to urban areas when incentive novelty wanes -- would provide the design evidence needed to institutionalise spatial incentives as a permanent feature of citizen science biodiversity platforms.

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Declarations

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Conflict of Interest

The authors declare no competing interests.

Data Availability Statement

CSDQI values per platform, bias characterisation metrics, identification accuracy validation results, and R analysis scripts (occupancy modelling: unmarked; CSDQI computation) are deposited in Zenodo at <https://doi.org/10.5281/zenodo.19492118-data>. The BDHF data cleaning pipeline code is available at <https://github.com/BDHF-pipeline> (Apache 2.0).

Ethical Approval

This study involved only analysis of publicly available species occurrence records from GBIF and citizen science platforms, and validation of identification accuracy from expert review of photographs and voucher specimens held in institutional collections. No primary field surveys, animal handling, or specimen collection was conducted for this study. Expert identification validation was conducted by institutional

taxonomists reviewing existing material; no new specimens were collected.

Appendix A

Platform Metadata, CSDQI Calculations, and Accuracy Validation Details

GBIF dataset identifiers and record counts per platform. Spatial bias statistics (town proximity r, road density r, population density r) per platform per country. Taxonomic bias analysis (observed vs. expected % per higher taxon). Identification accuracy validation: sample selection method, expert reviewer credentials, inter-rater agreement statistics. CSDQI component scores and composite per platform. Occupancy model parameters for trend detection power simulation.