Julius-Maximilians-
UNIVERSITÄT
WÜRZBURG

Chair for
INFORMATICS I
Efficient Algorithms and
Knowledge-Based Systems

Institute for Informatics

Using the A* Algorithm to Find Optimal Sequences for Area Aggregation

Dongliang Peng[1], Alexander Wolff[1], Jan-Henrik Haunert[2]

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Map Generalization...

...is about selecting and representing information on a map.

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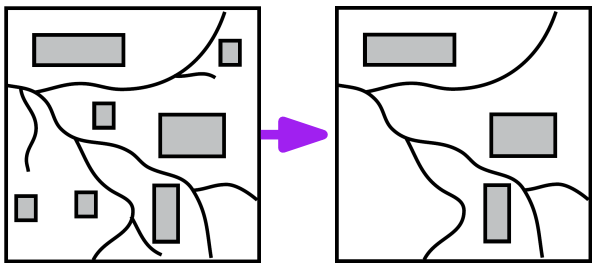
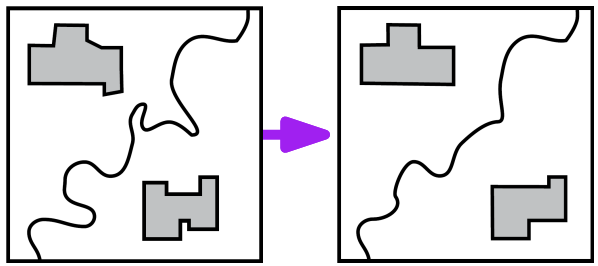
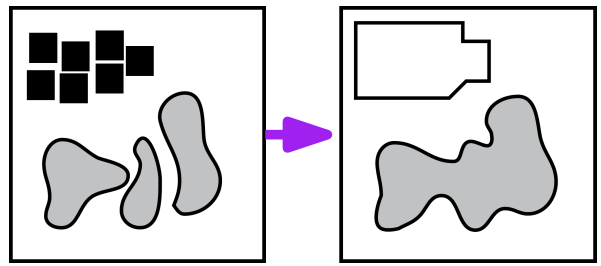
Typical generalization operators (ESRI 1996):



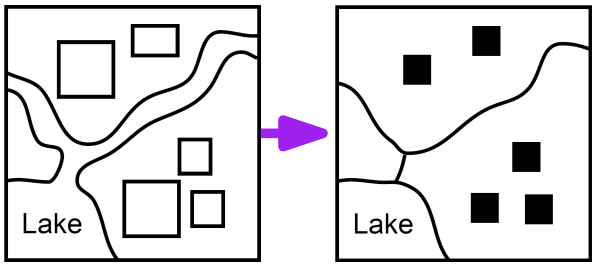
Elimination



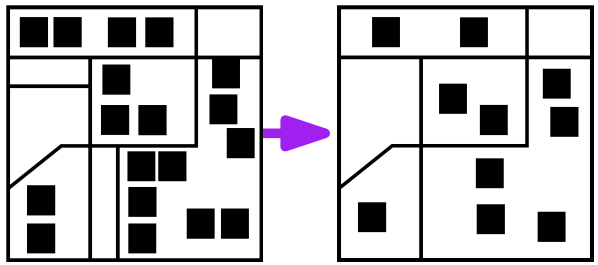
Simplification



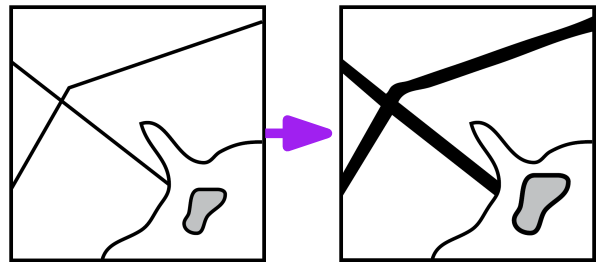
Aggregation



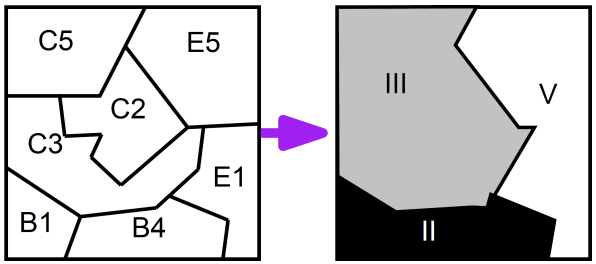
Collapse



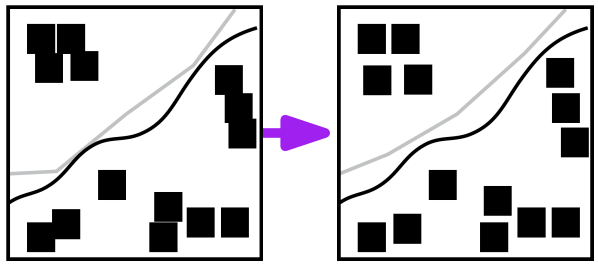
Typification



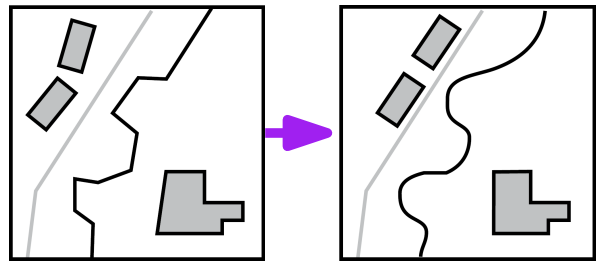
Exaggeration



Classifi. and symboli.



Displacement



Refinement

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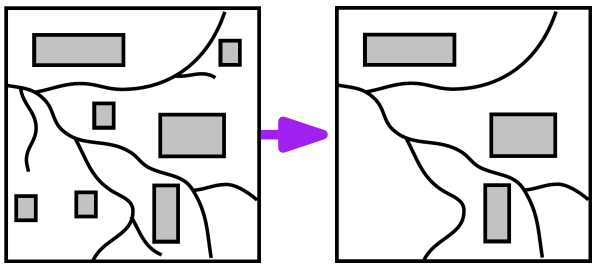

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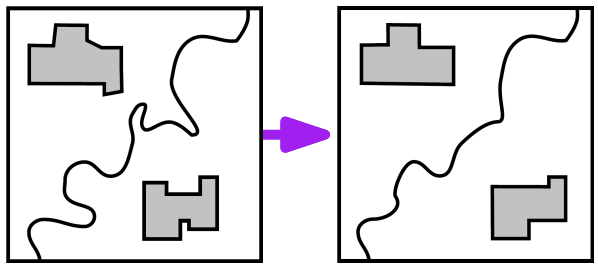
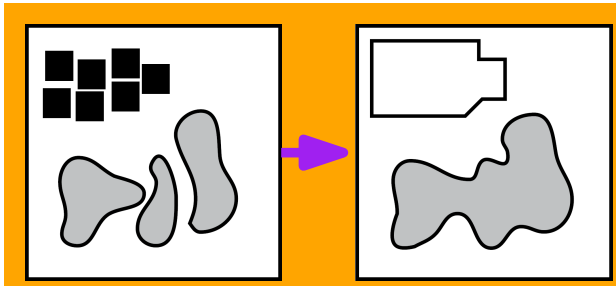
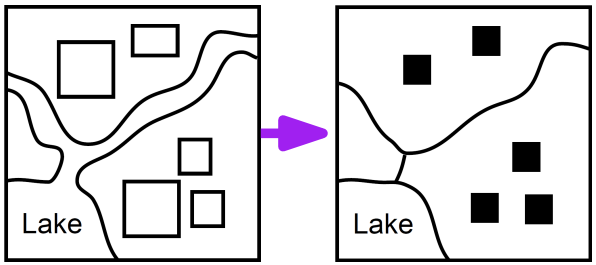


Simplification



Aggregation



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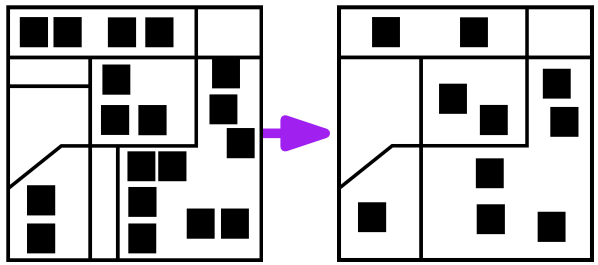

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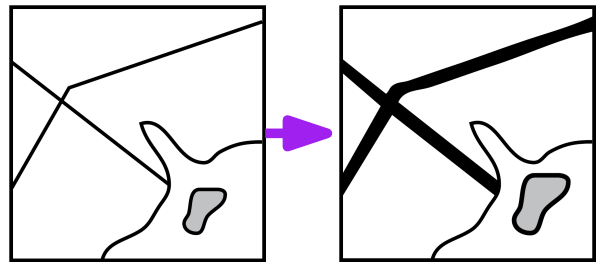
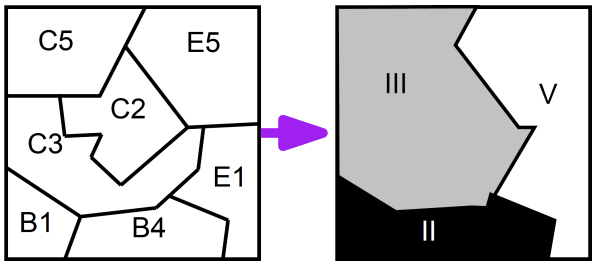


Exaggeration



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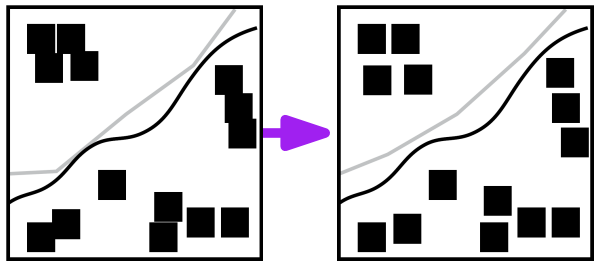

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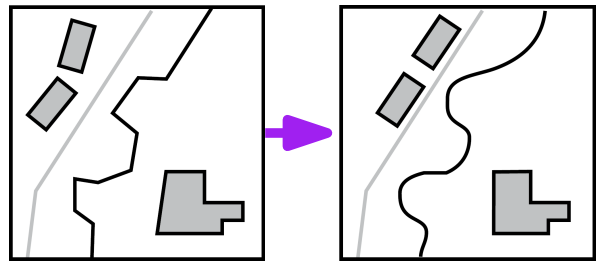
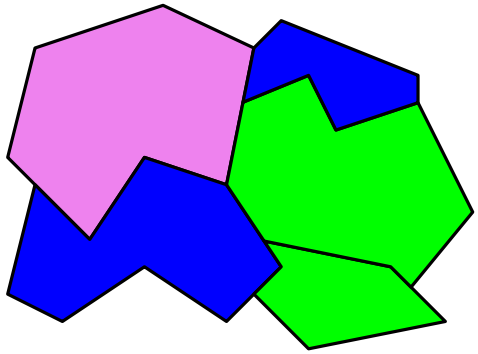
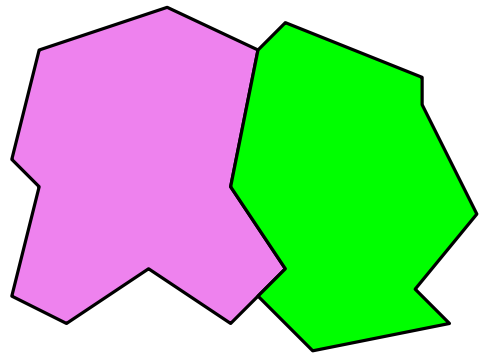


Refinement

Research Problem





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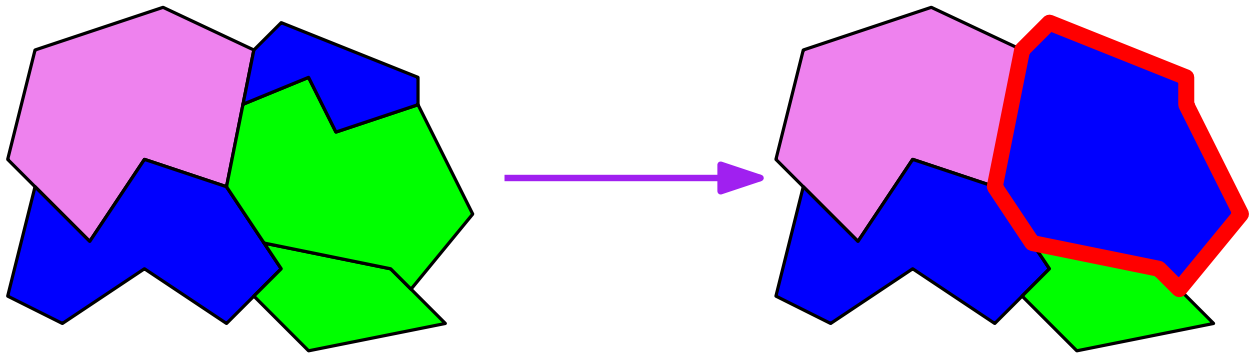

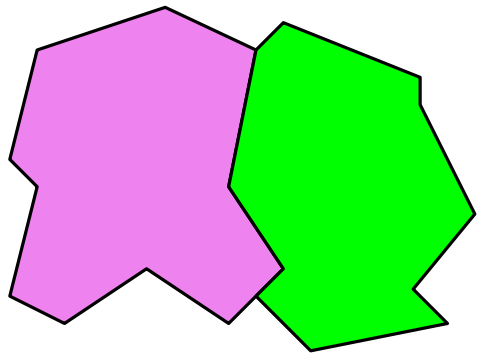

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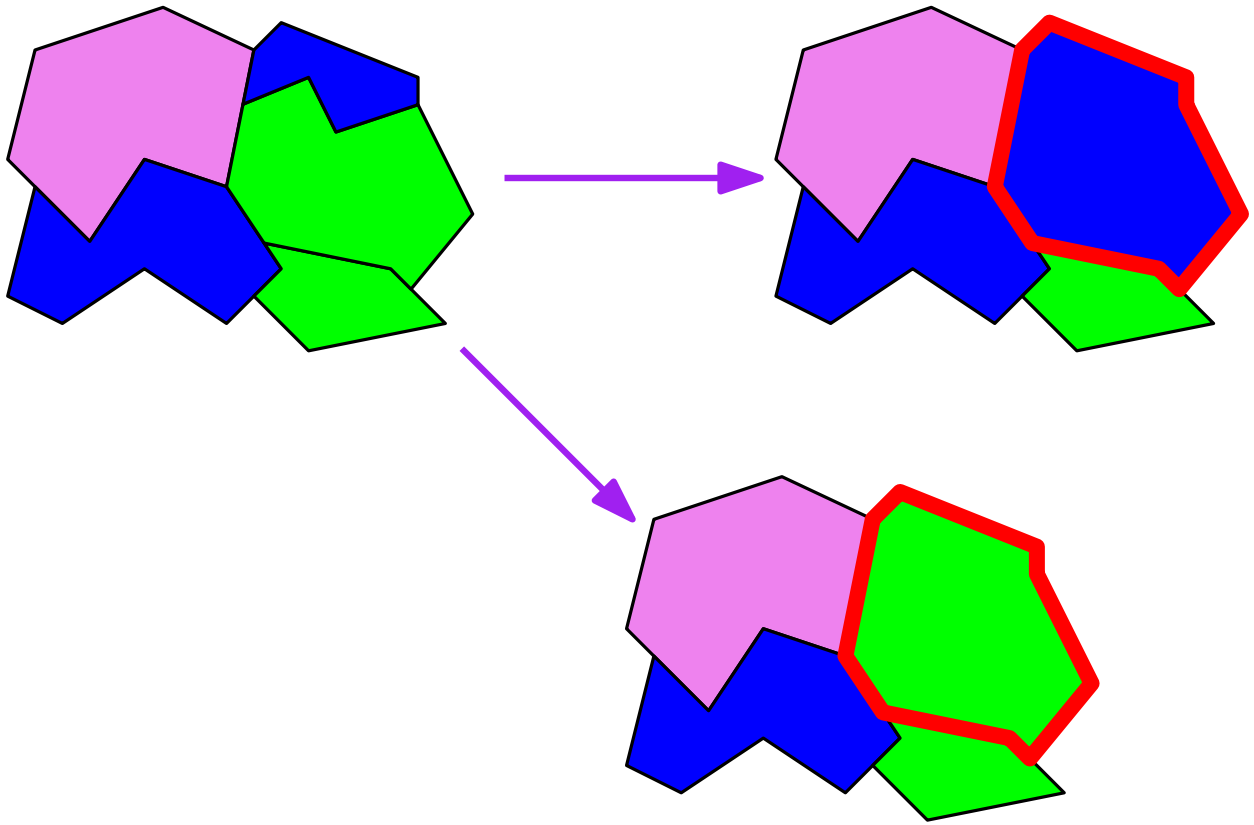

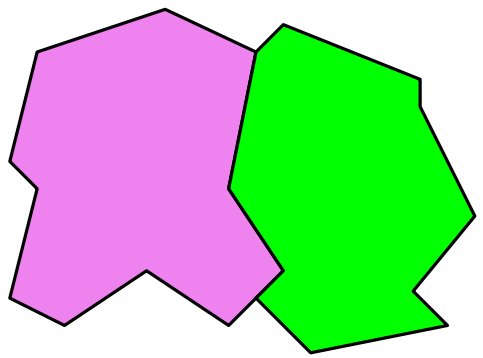

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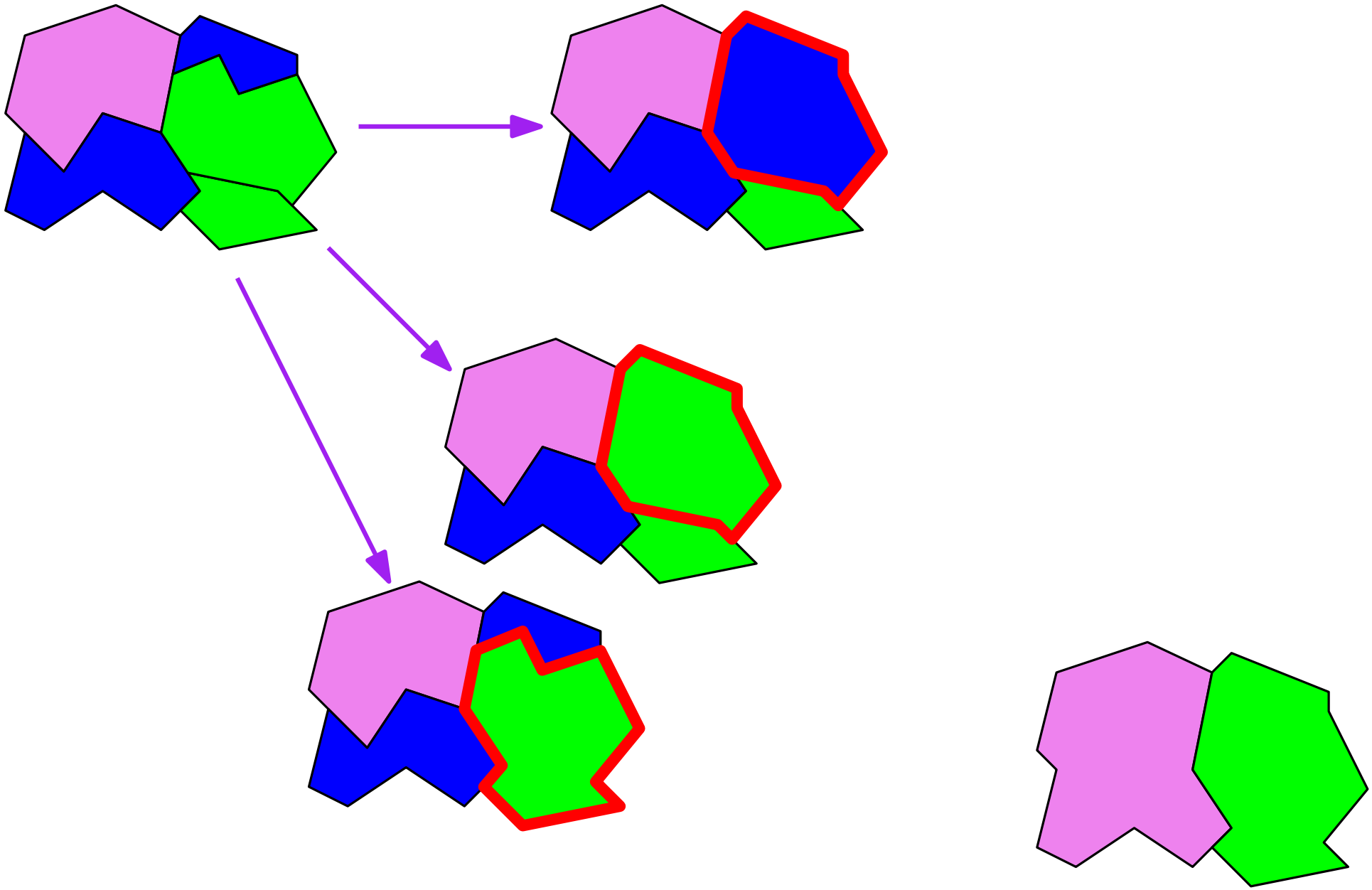

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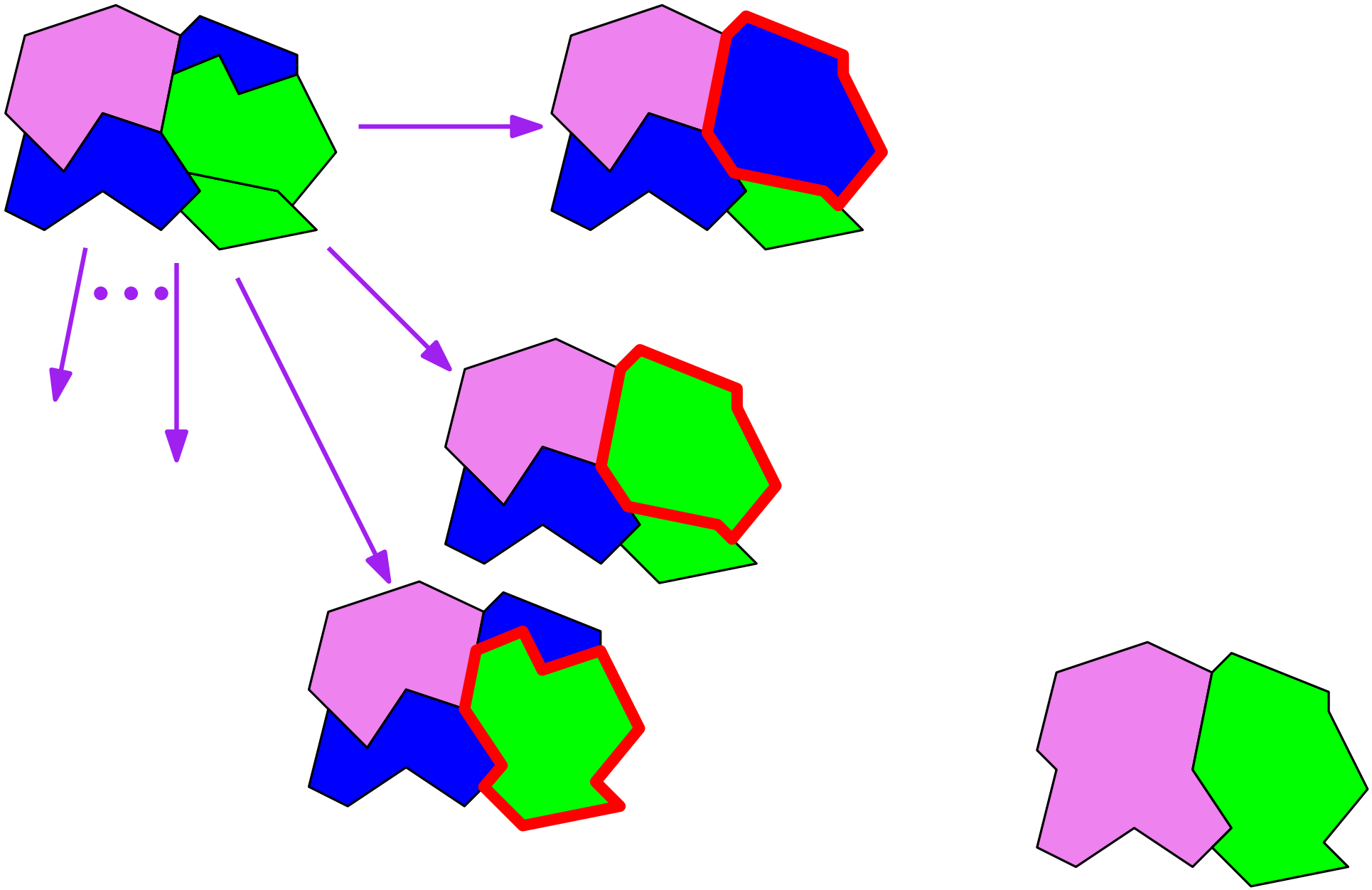

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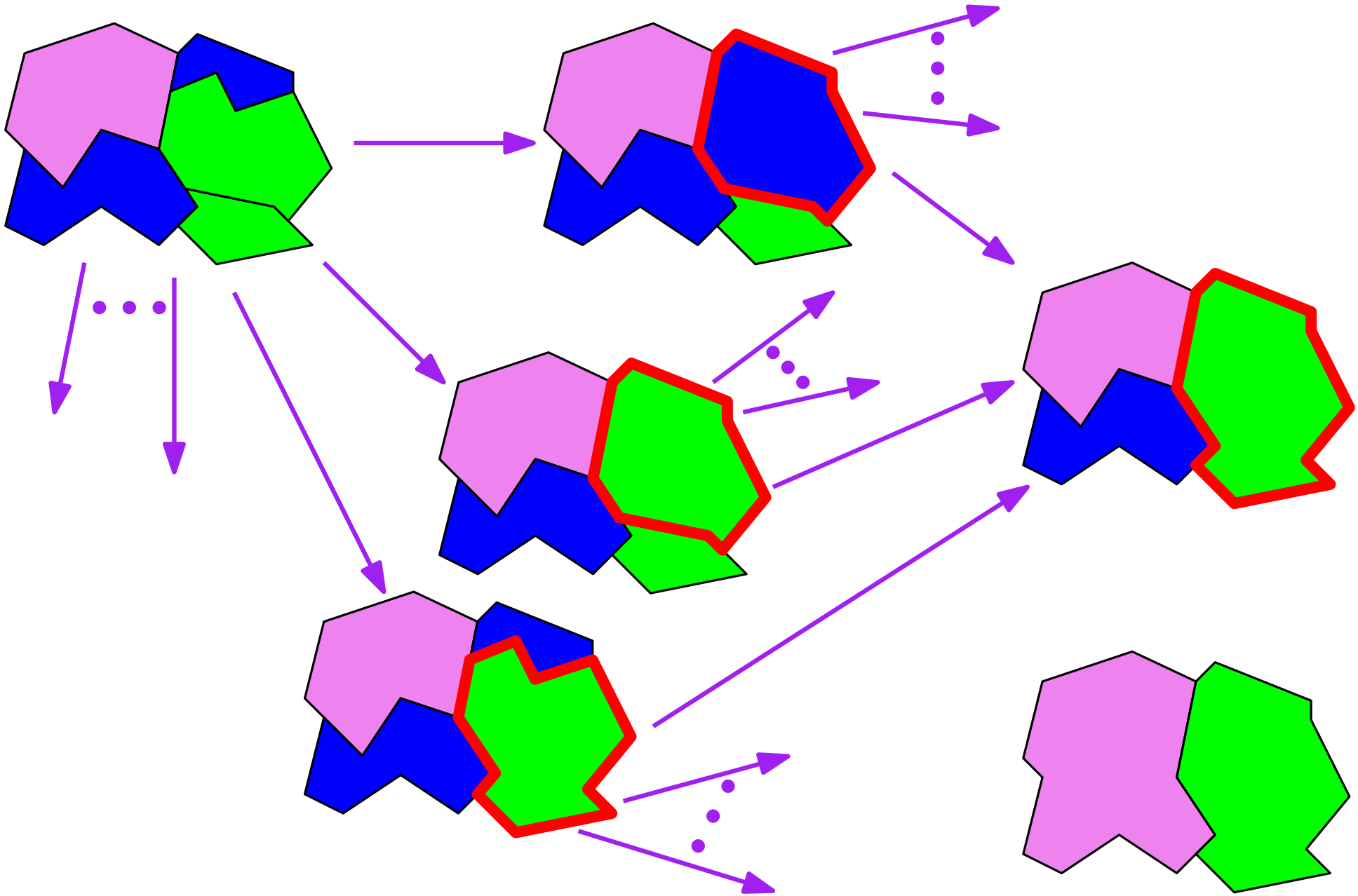

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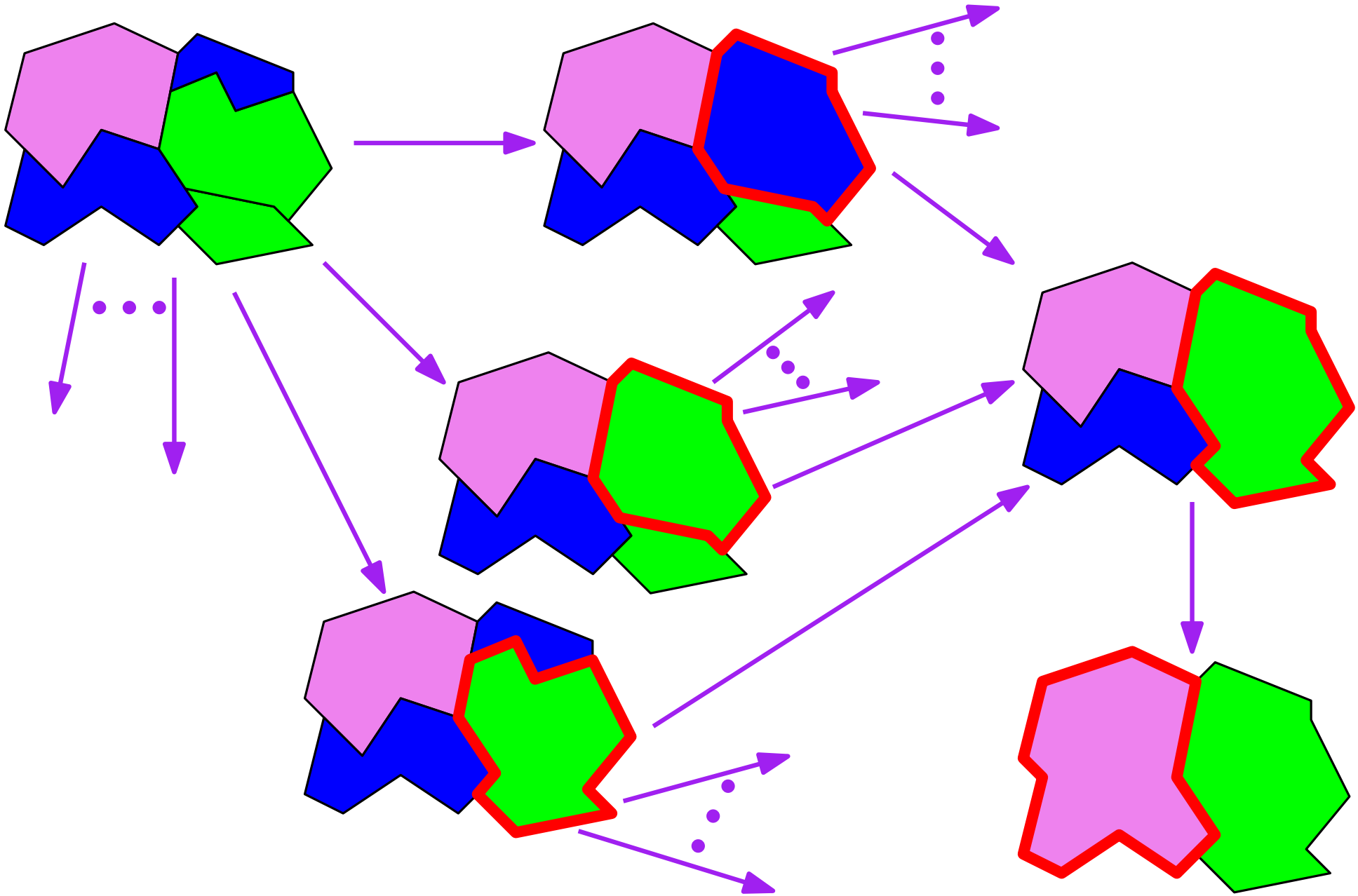

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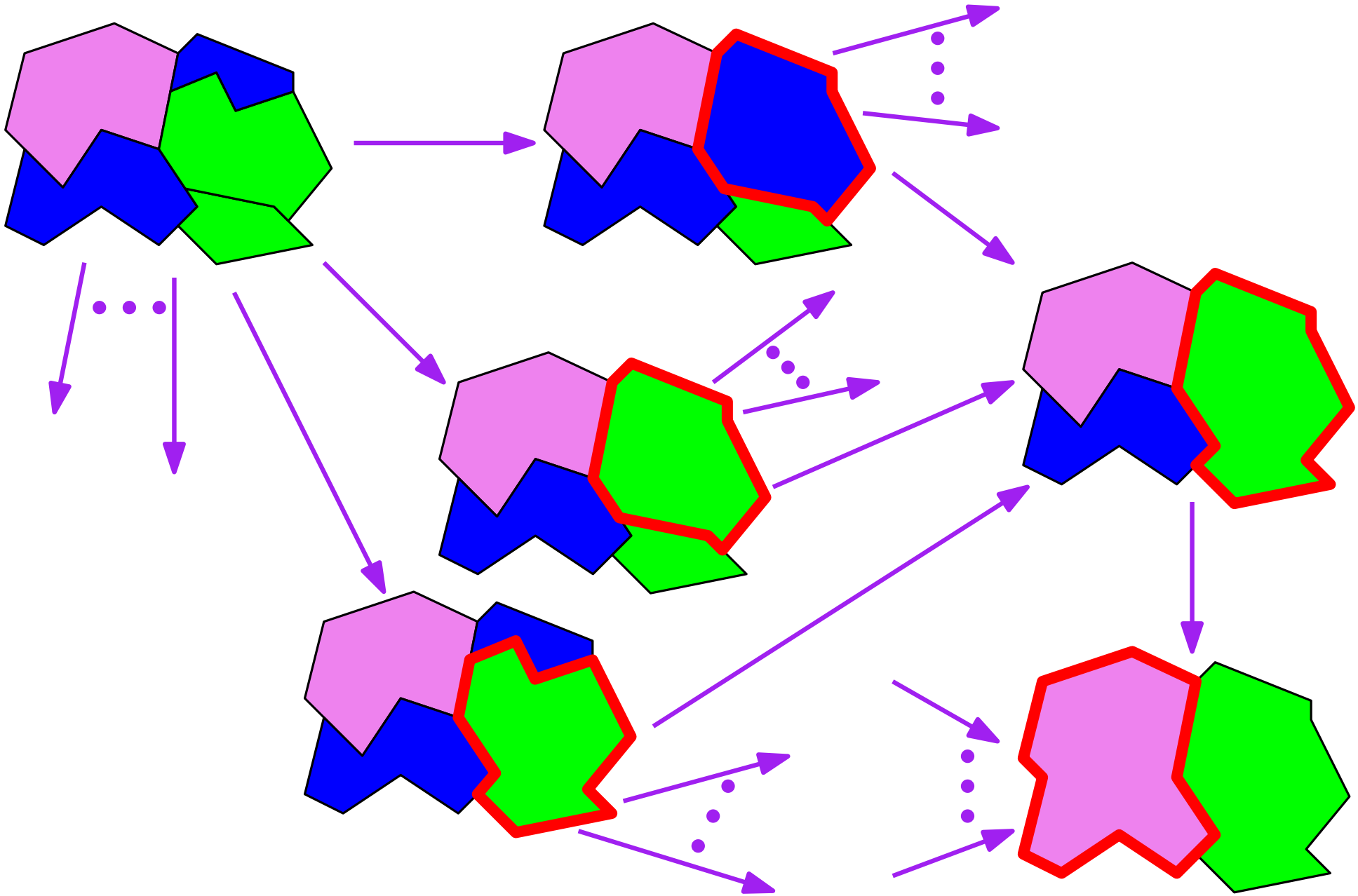
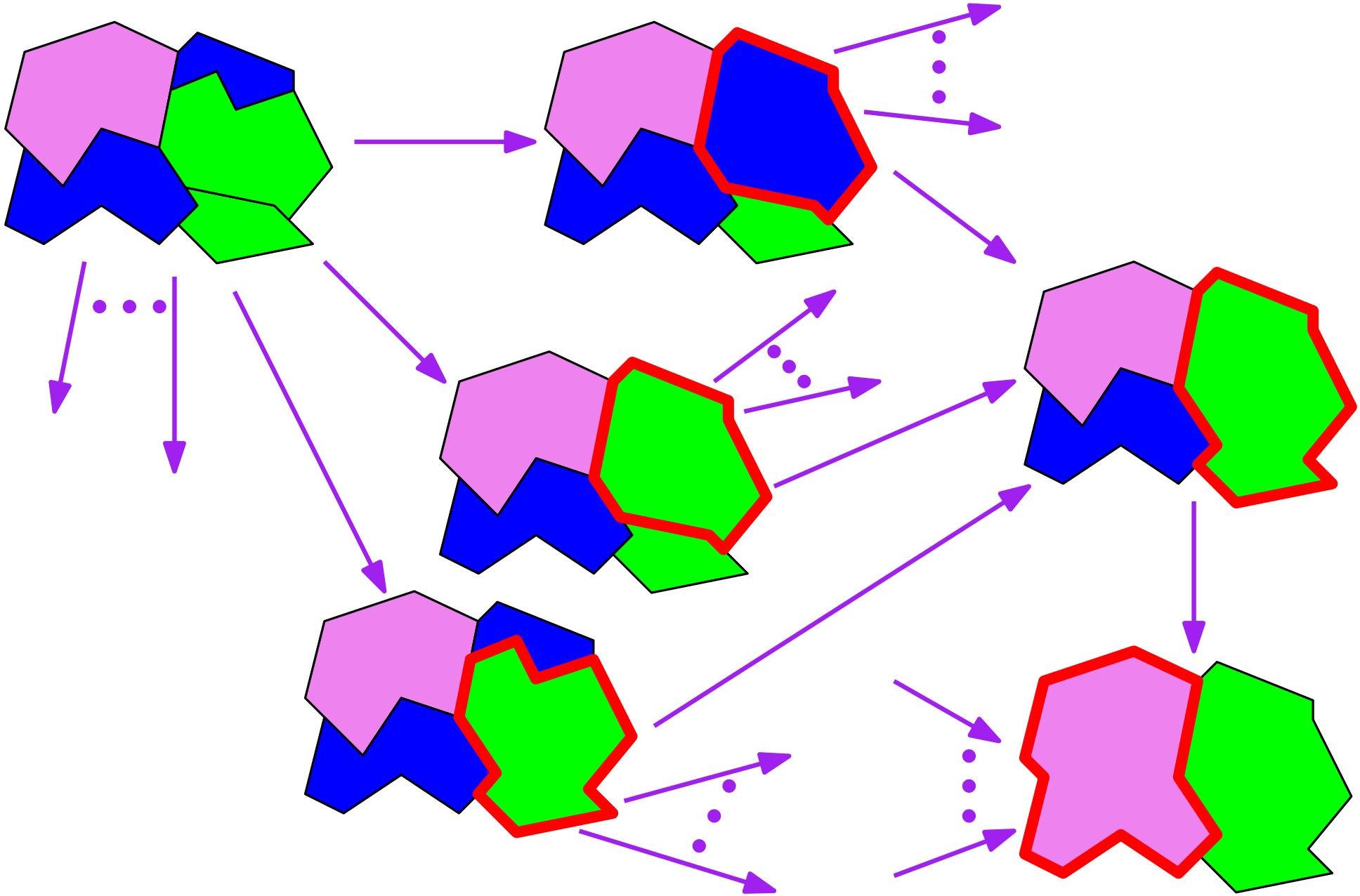


Research Problem

Given aggregation costs:

What is an optimal sequence?



Standard Approach for Dynamic Maps

- Users zoom in and out to read digital maps

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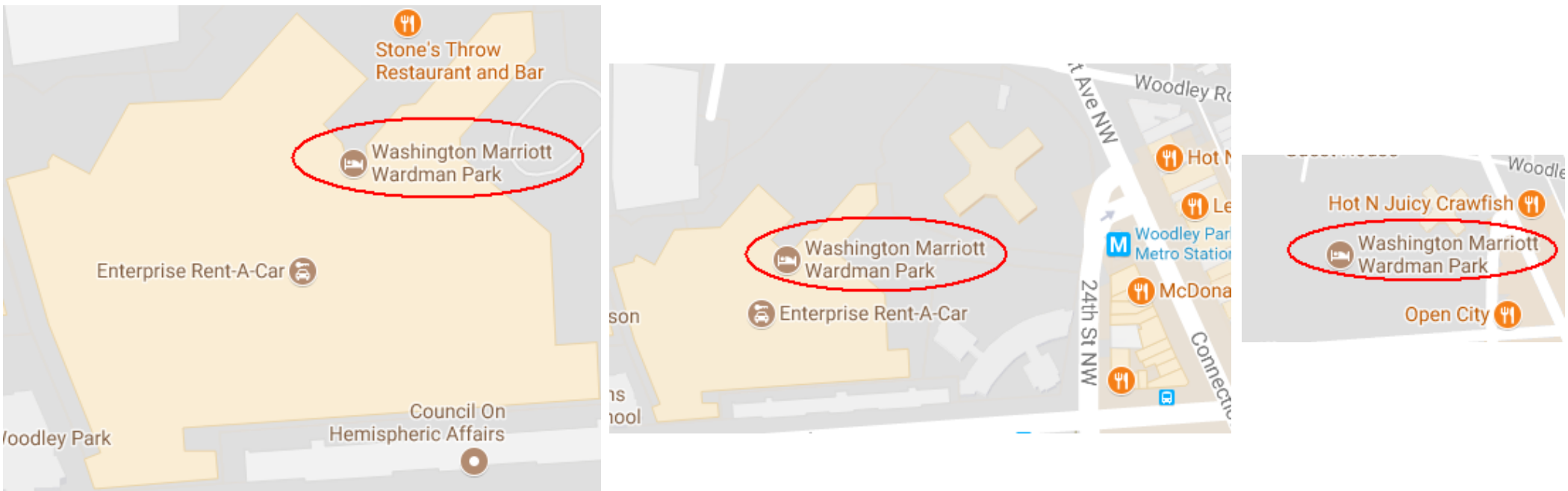


zoom out

(Google Maps)

Standard Approach for Dynamic Maps

- Users zoom in and out to read digital maps
- Multi-Representation Databases (MRDB) support Levels of Detail (LODs) (Hampe et al. 2004)

Expect continuous change!

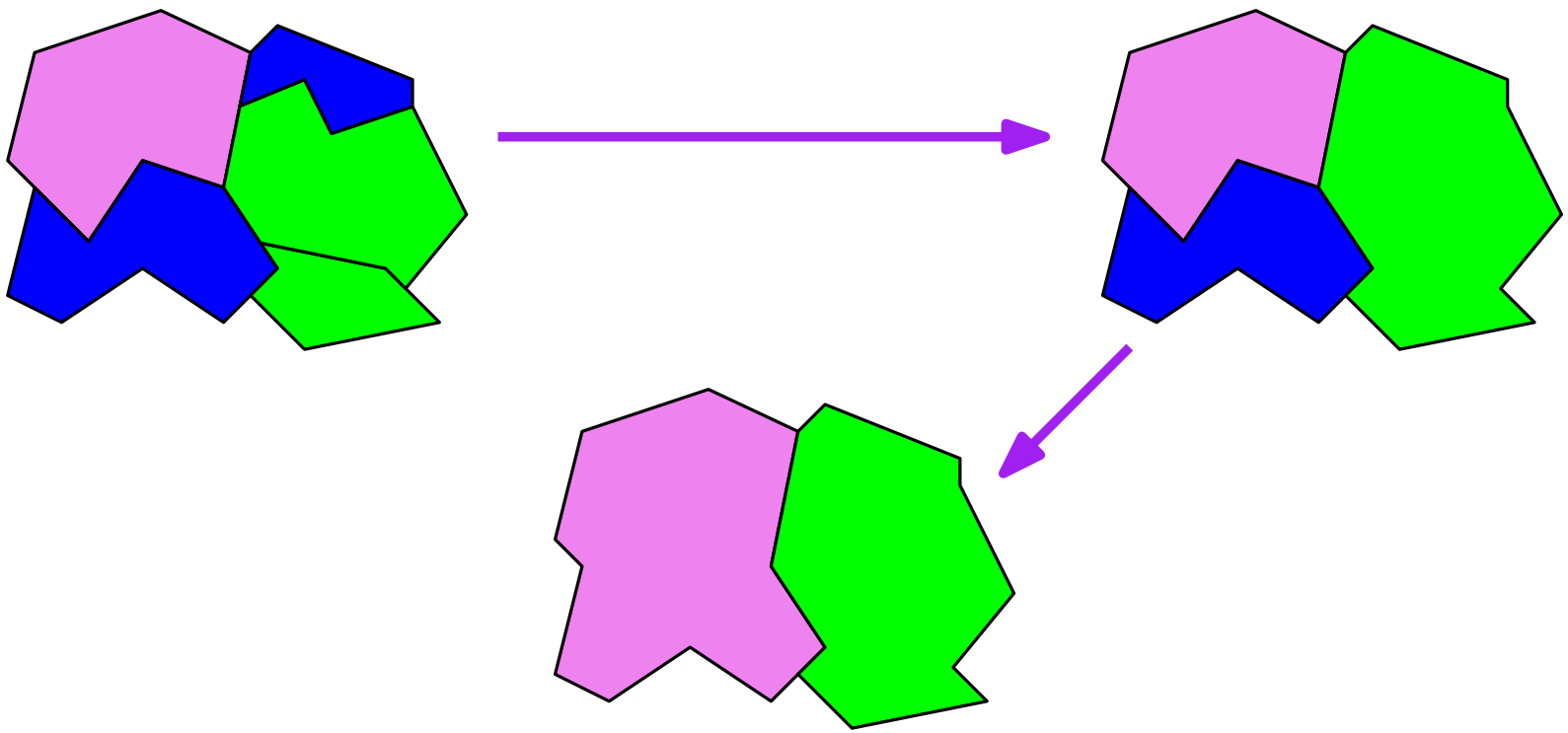
zoom out

(Google Maps)

Outline

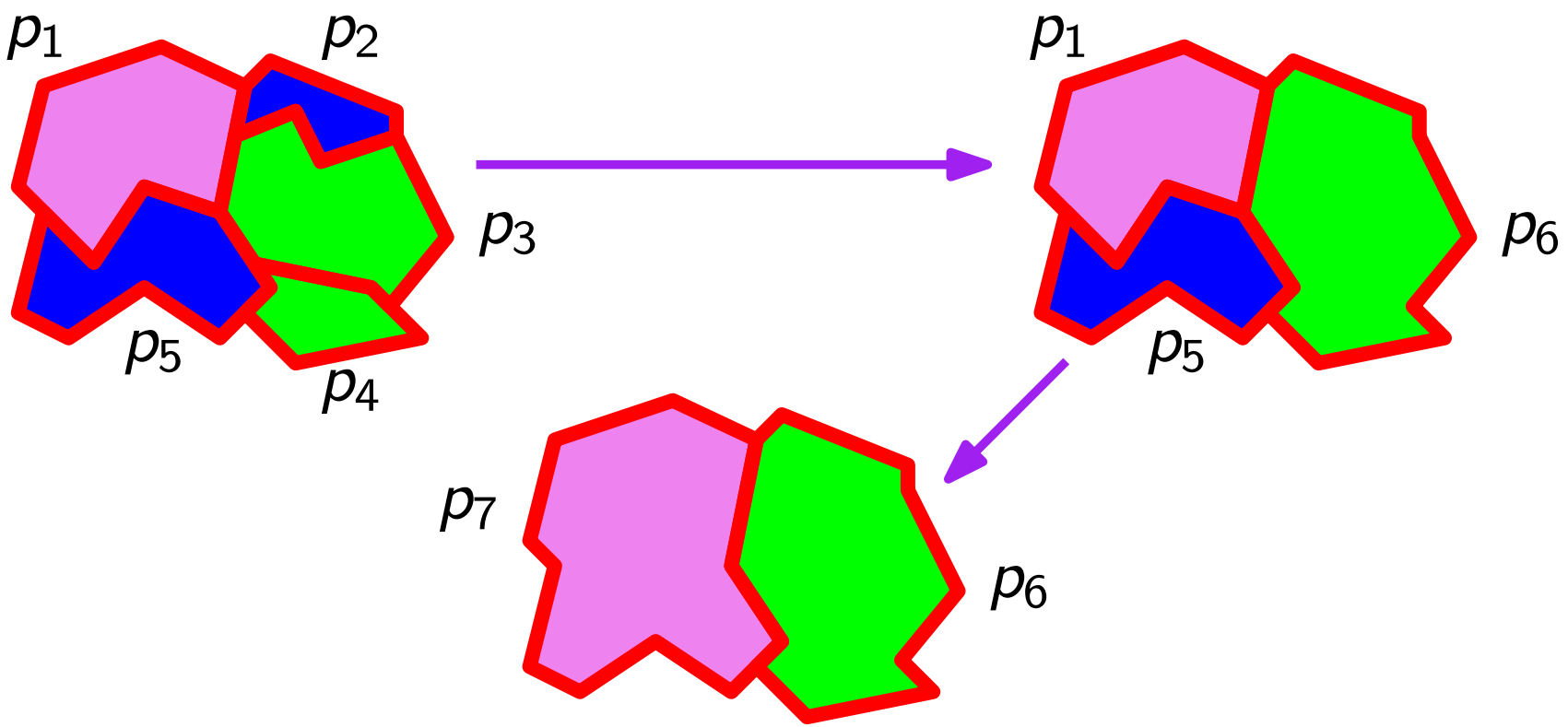
- Introduction
- Methodology
- Case Study
- Concluding Remarks

Preliminaries



Preliminaries

Patch p_i: a set of land-cover areas whose union is connected



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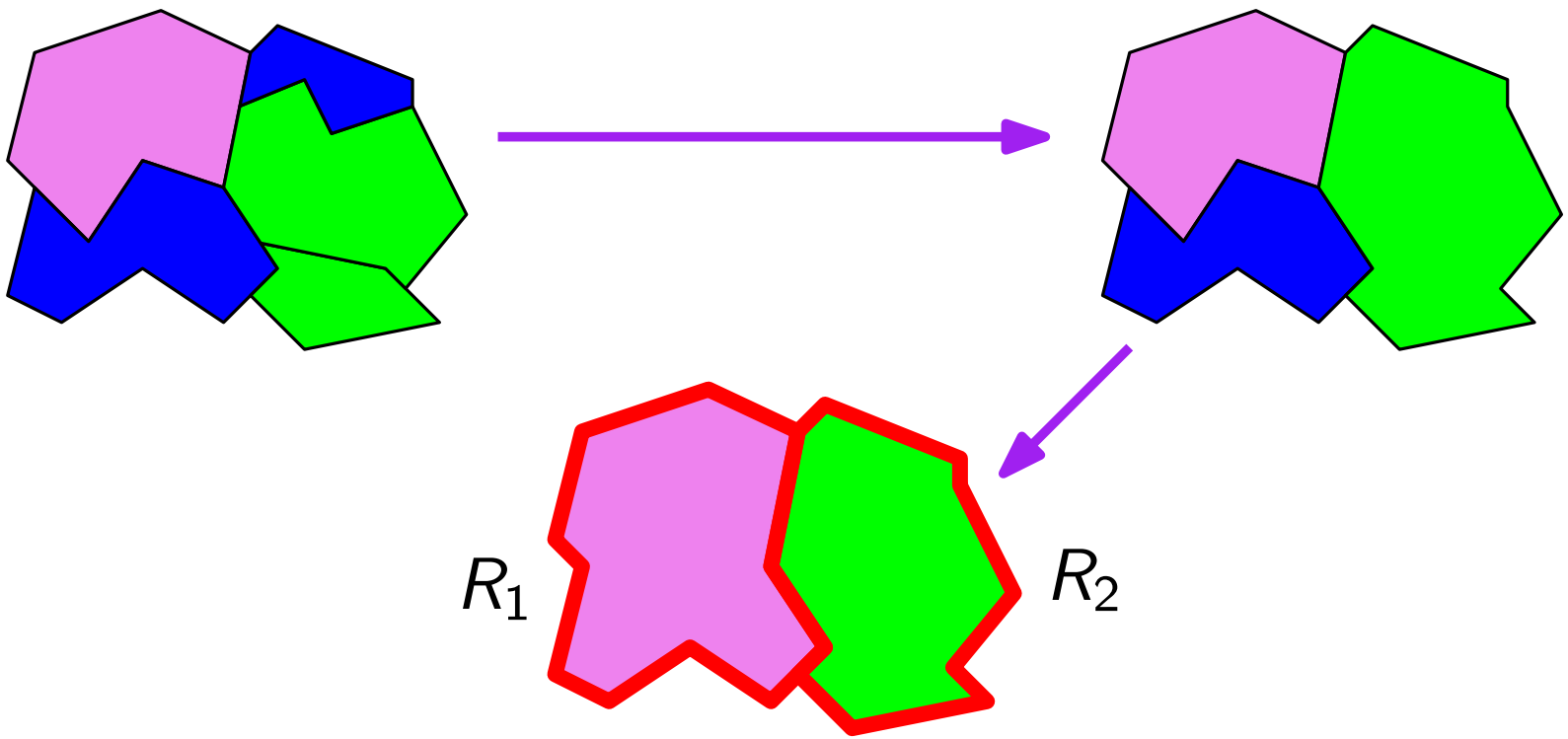
Patch p_i: a set of land-cover areas whose union is connected

Region R_i: an area on the goal map

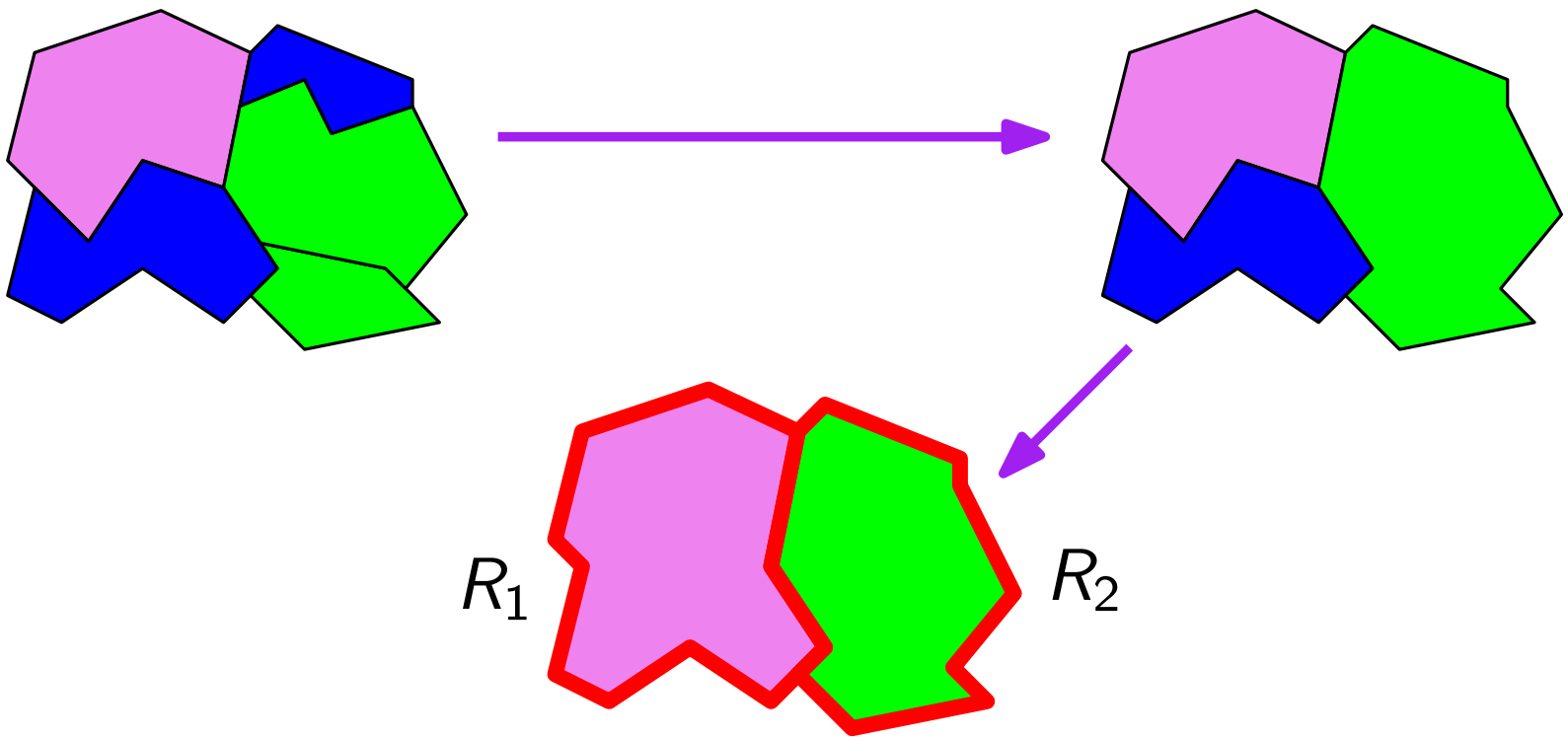


Preliminaries

Patch p_i: a set of land-cover areas whose union is connected

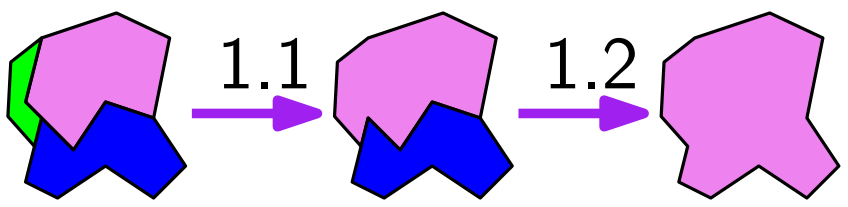
Region R_i: an area on the goal map

Aggregate the smallest patch with one of its neighbours at each step

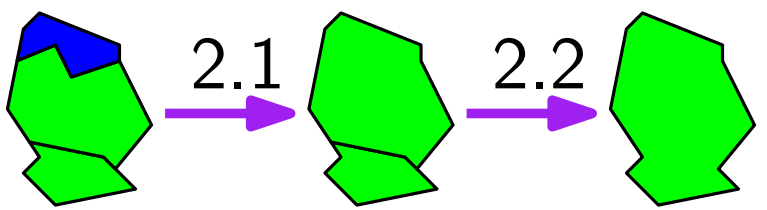


Integrate Aggregation Sequences

according to the order of smallest areas



sequence of the pink region



sequence of the green region

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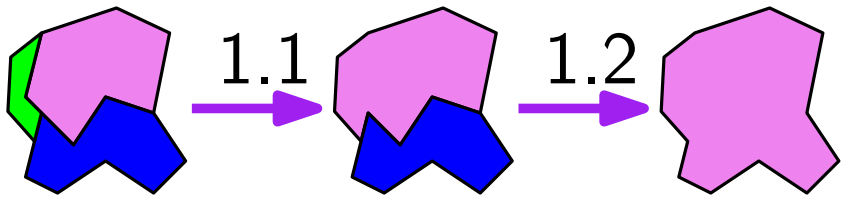

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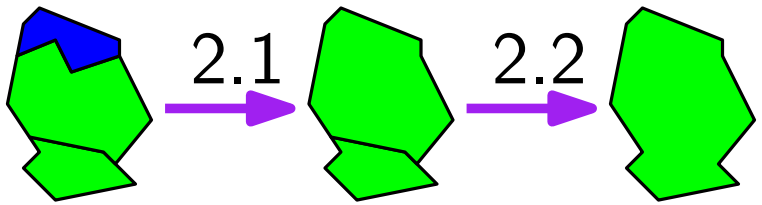

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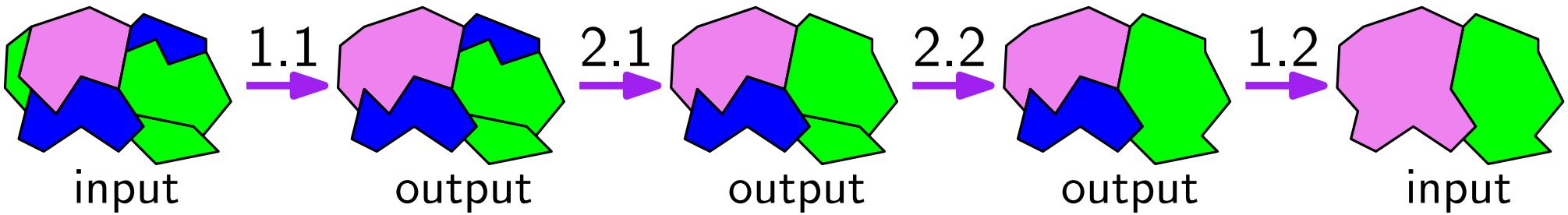
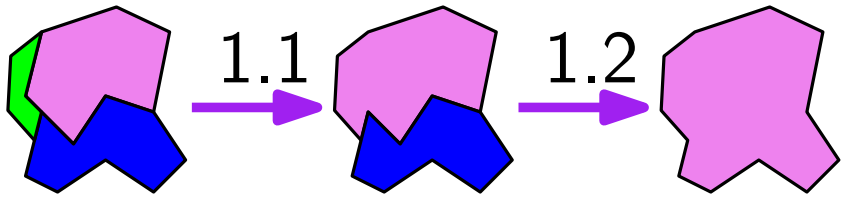


integrated sequence of the two regions

Integrate Aggregation Sequences

according to the order of smallest areas



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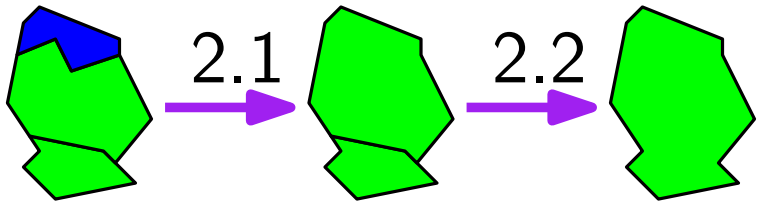

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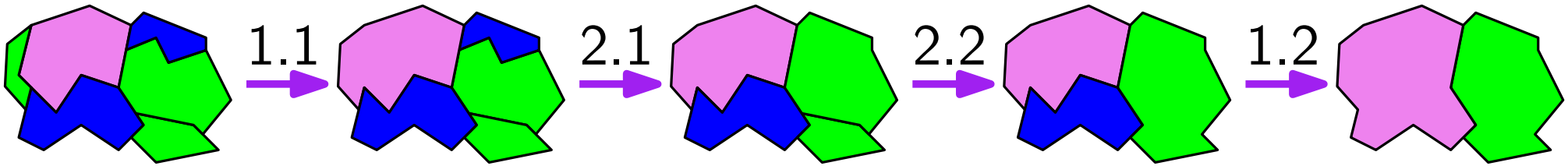
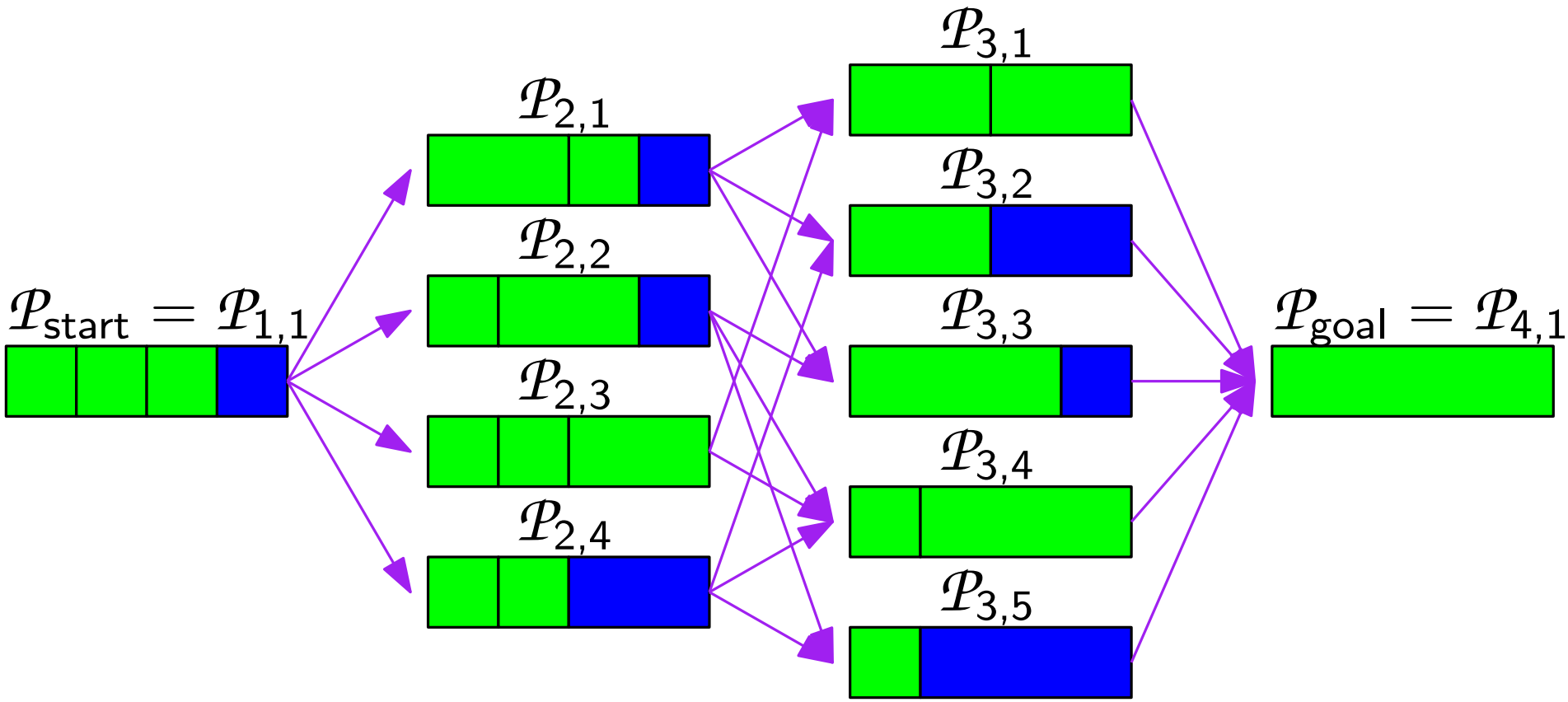


integrated sequence of the two regions

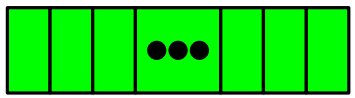
Subdivision

Subdivision $\mathcal{P}_{t,i}$: a set of patches subdividing a single region R



Number of Subdivisions

layer 1

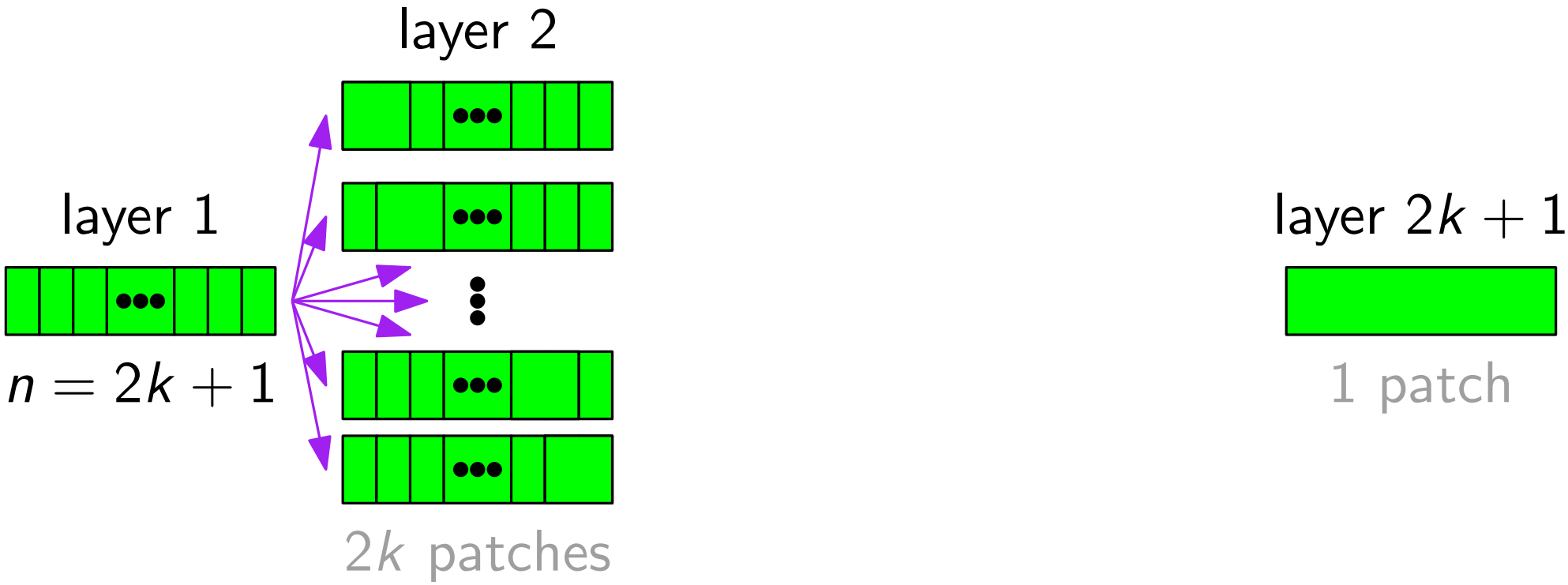


$n = 2k + 1$

layer $2k + 1$

1 patch

Number of Subdivisions



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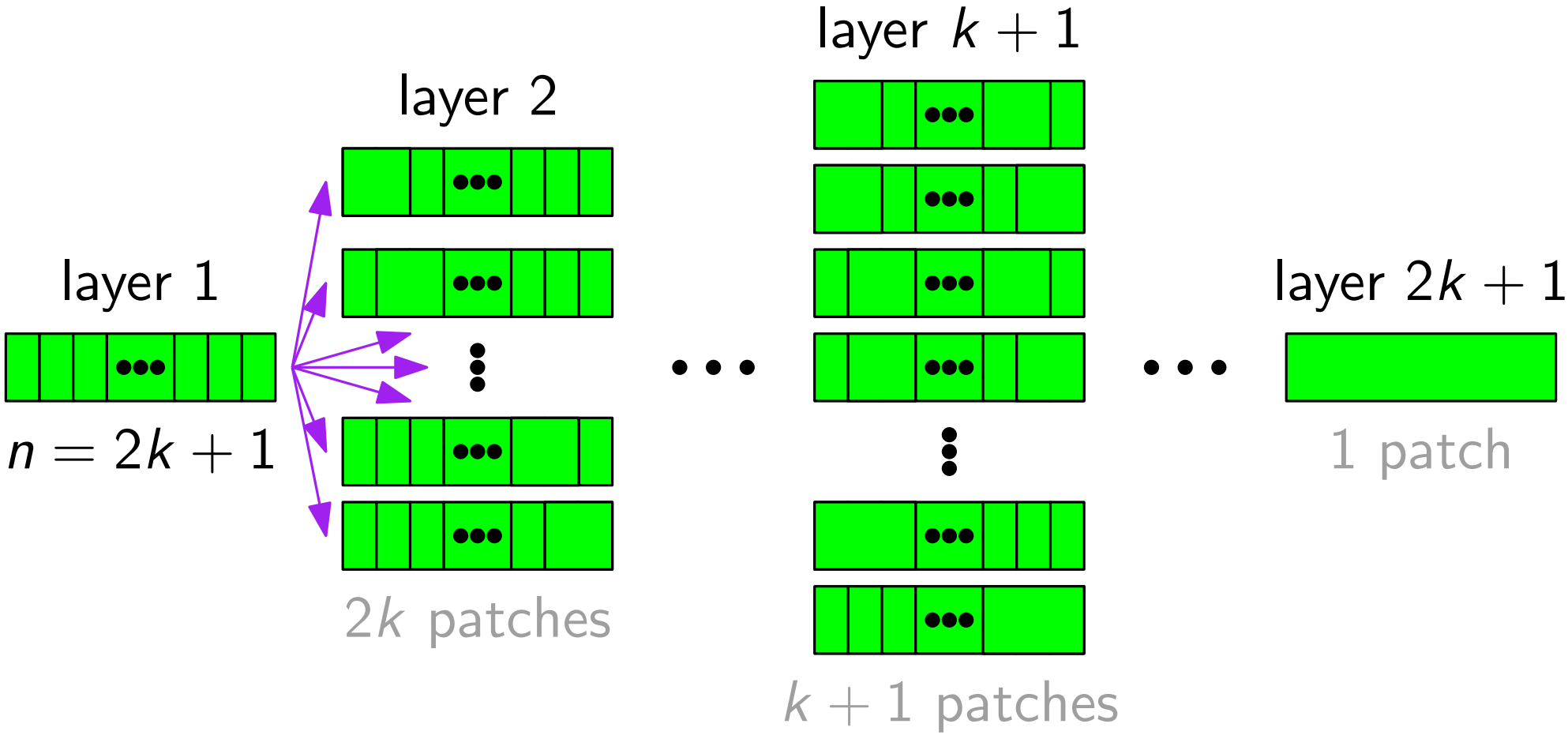

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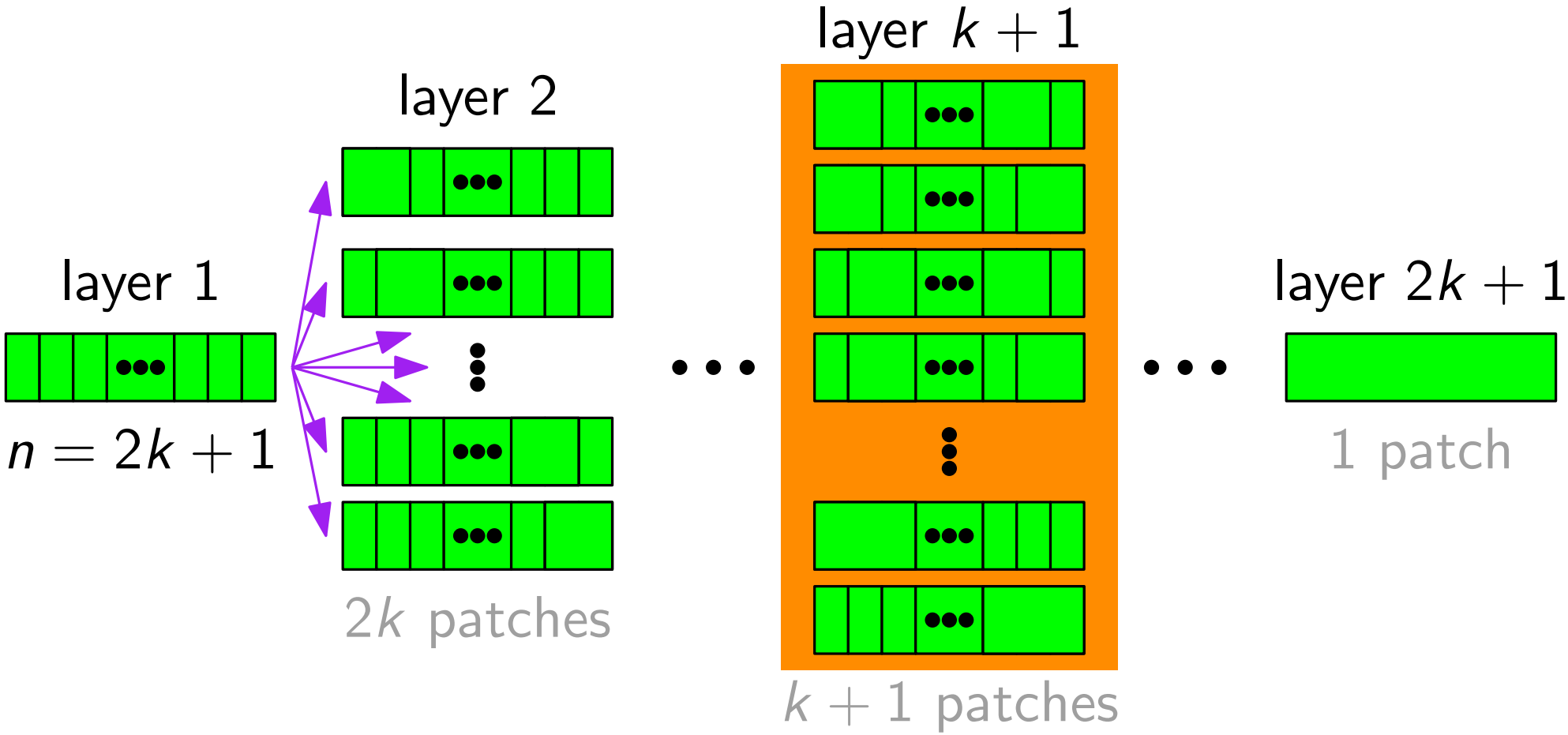
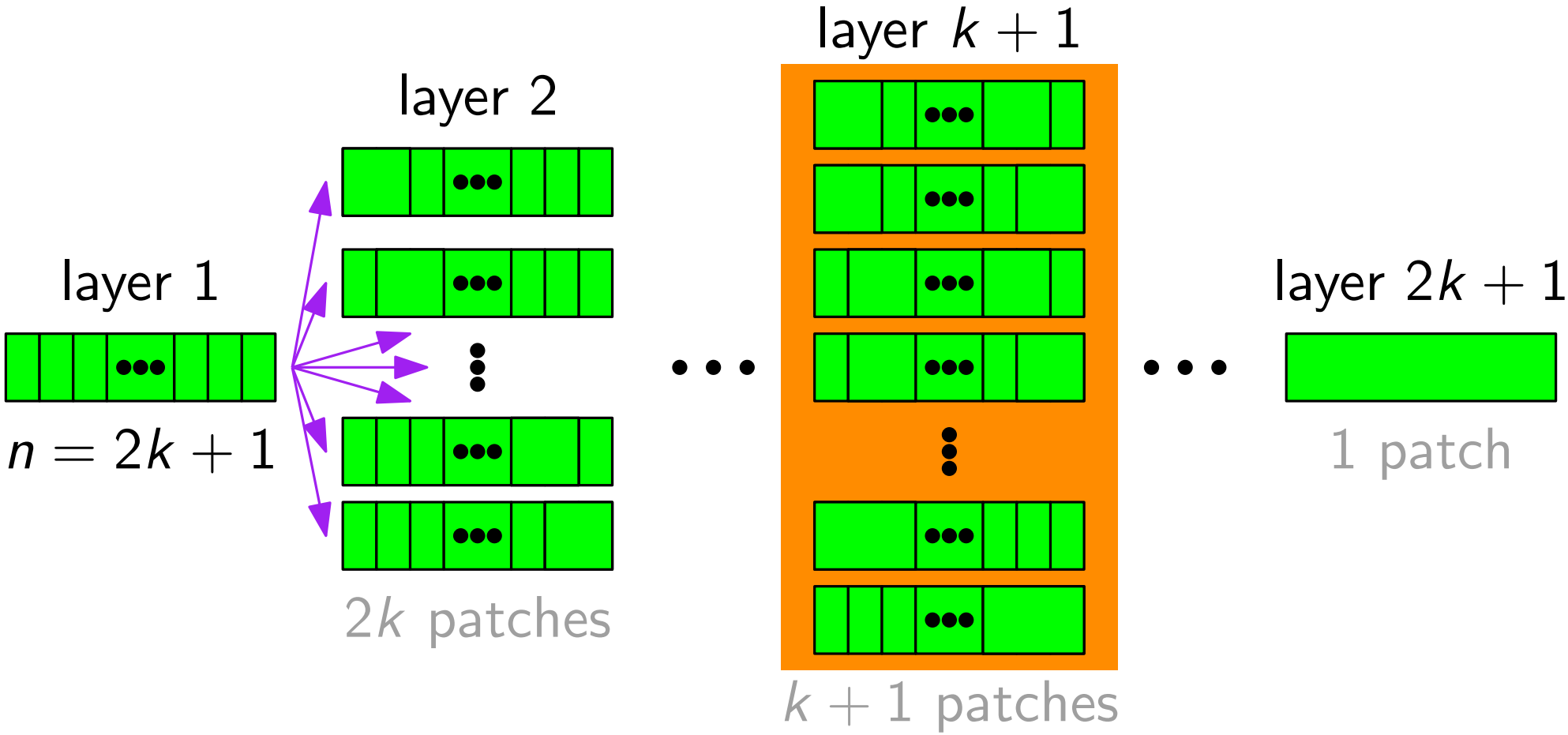


At layer $k+1$, remove k of the $2k$ intermediate sticks:
$\binom{2k}{k} \geq 2^k = 2^{(n-1)/2}$ subdivisions

Number of Subdivisions

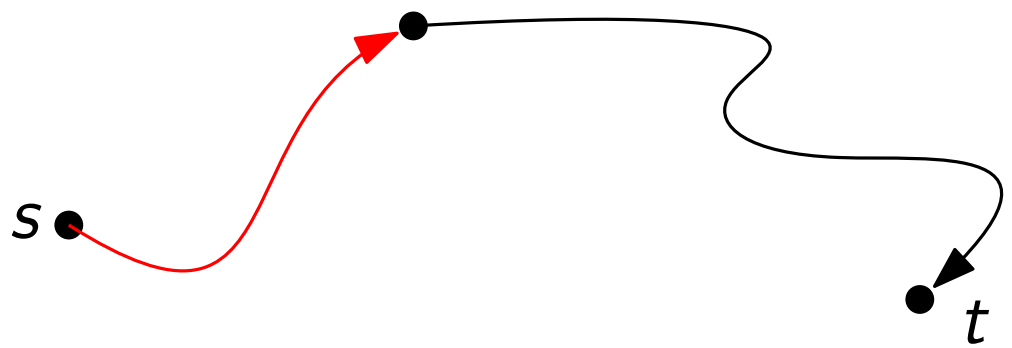


At layer $k+1$, remove k of the $2k$ intermediate sticks:
$\binom{2k}{k} \geq 2^k = 2^{(n-1)/2}$ subdivisions

$\Rightarrow$ The number of subdivions is at least *exponential* in the number n of polygons in layer $k+1$.

A* Algorithm

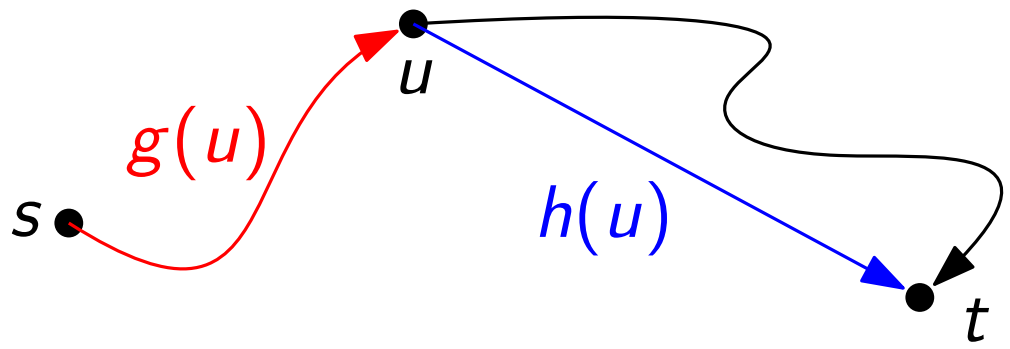
- A best-first search algorithm to find a path from a source node s to a target node t



A* Algorithm

- A best-first search algorithm to find a path from a source node s to a target node t

- Cost function: $F(u) = g(u) + h(u)$
  - $g(u)$: exact cost of s-u path
  - $h(u)$: estimated cost of shortest u-t path



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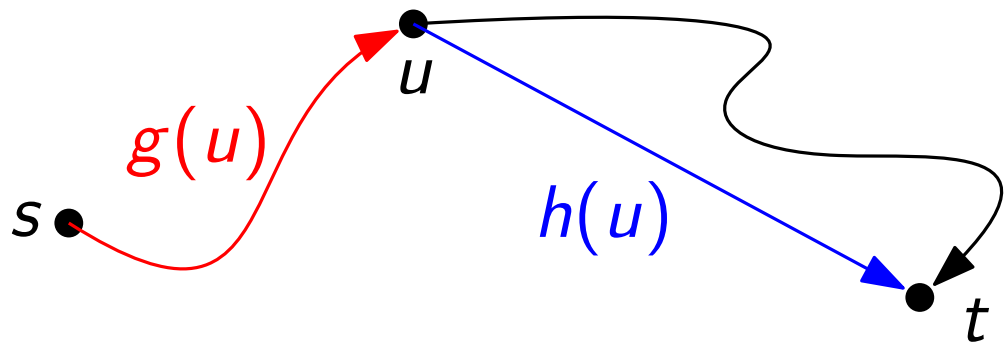


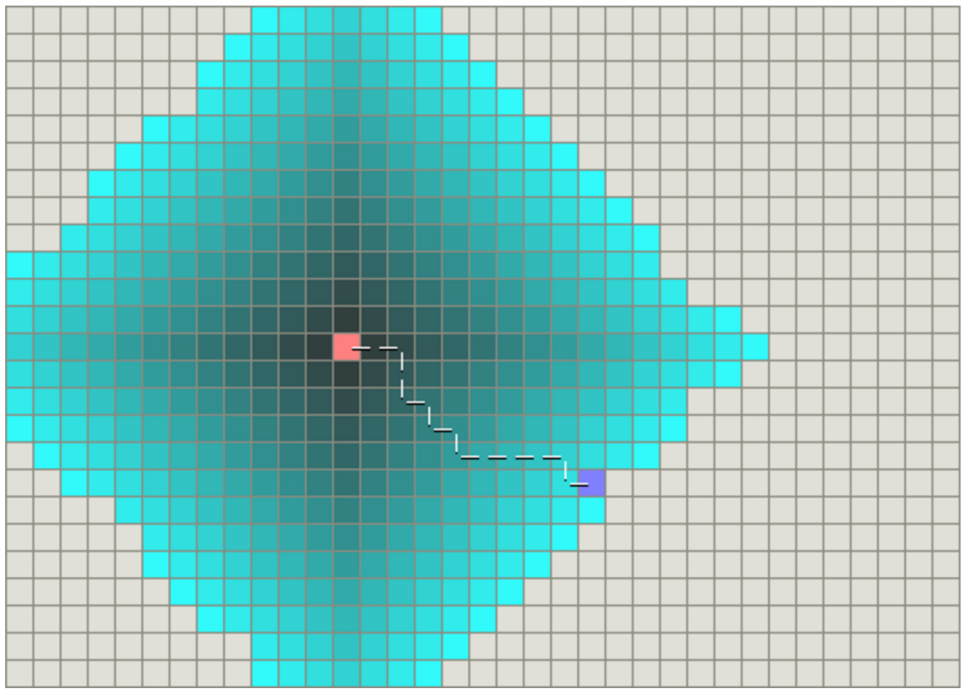
- Guarantees a shortest path if $h(u)$ never overestimates.

Shortest-Path Algorithms

Find shortest path from pink cell to blue cell

(Amit's A* Pages)

Dijkstra's algorithm:



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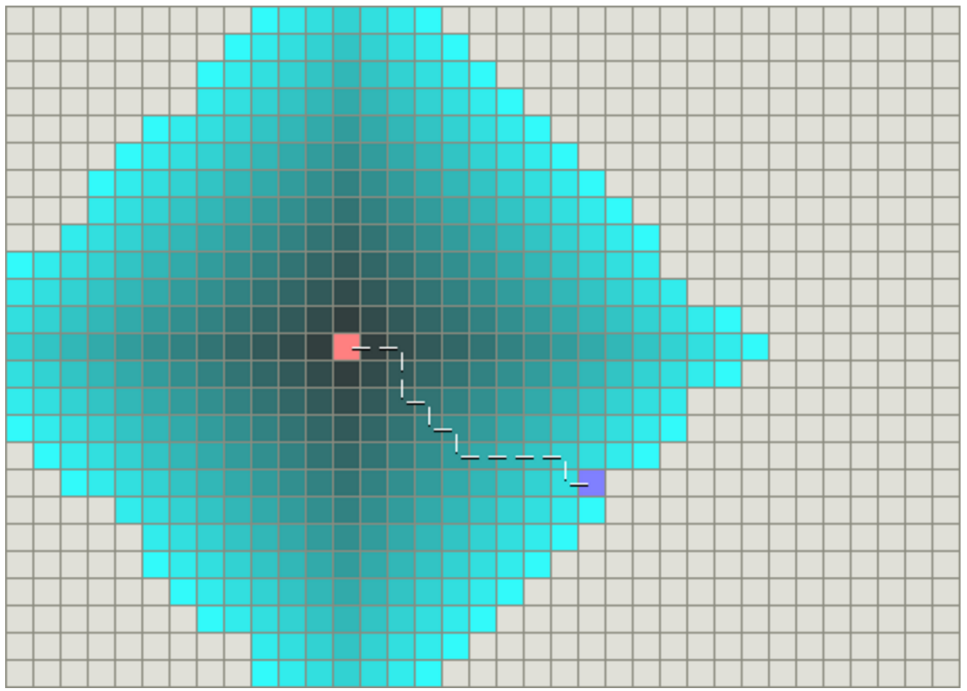
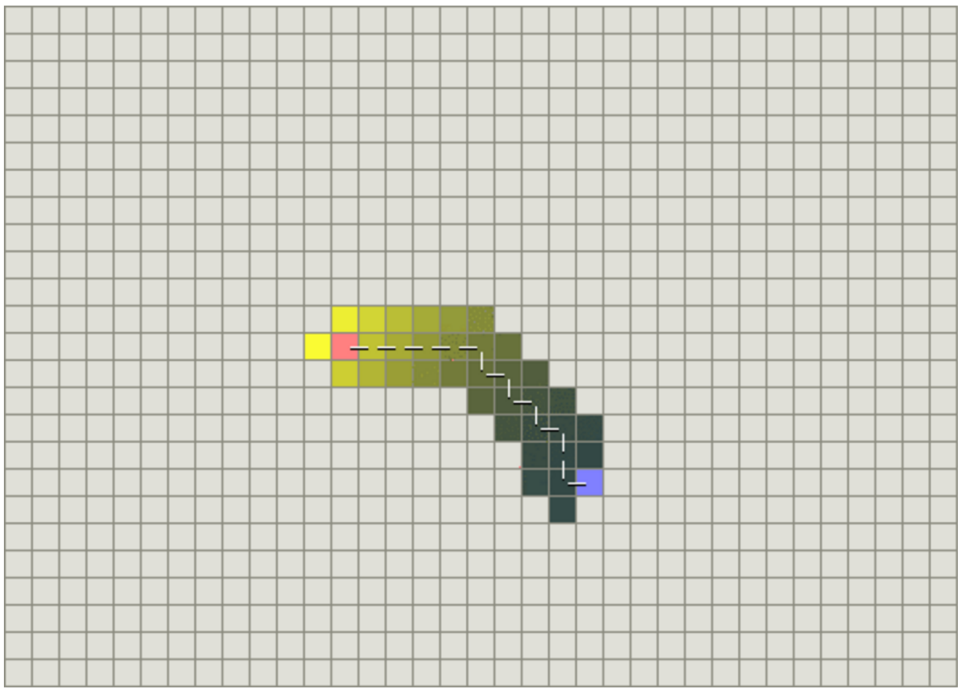
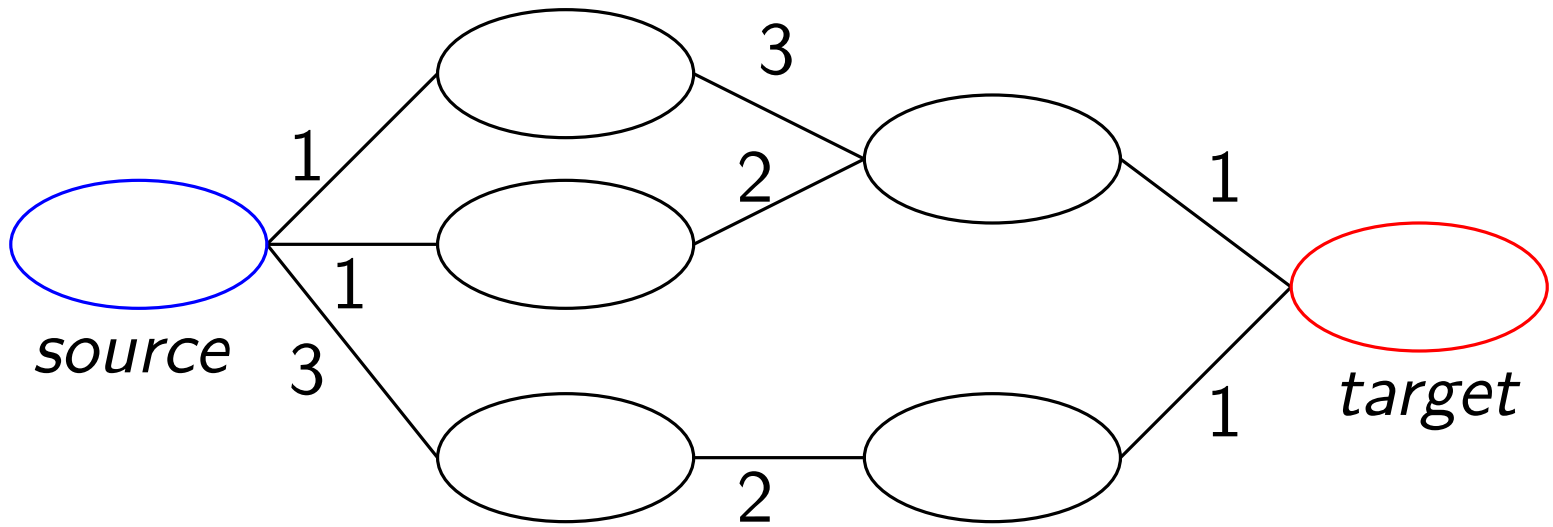


A* algorithm:

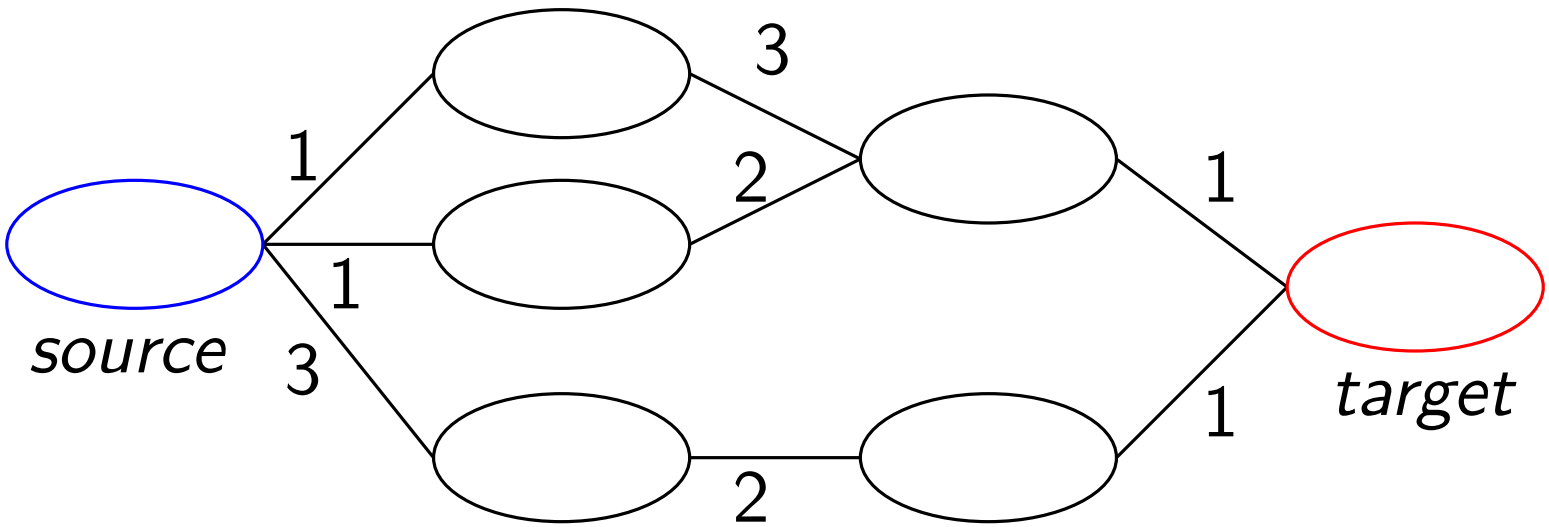


A* Algorithm

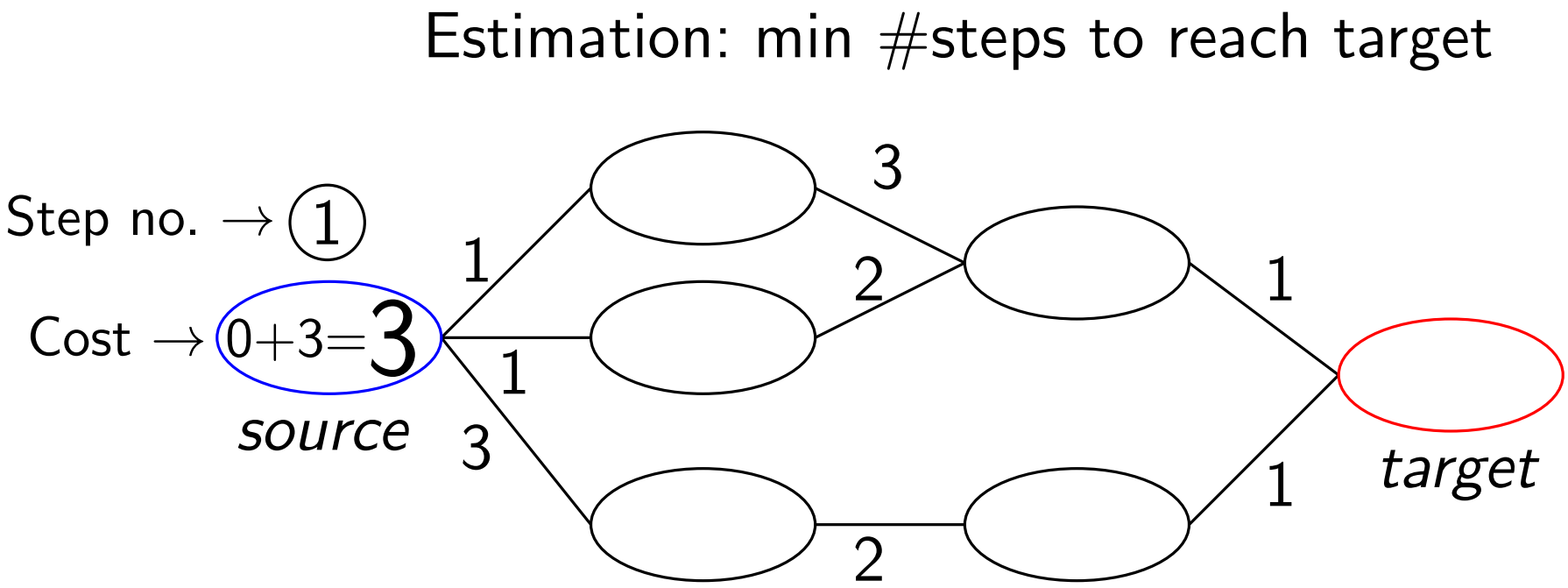


A* Algorithm

Estimation: min #steps to reach target



A* Algorithm



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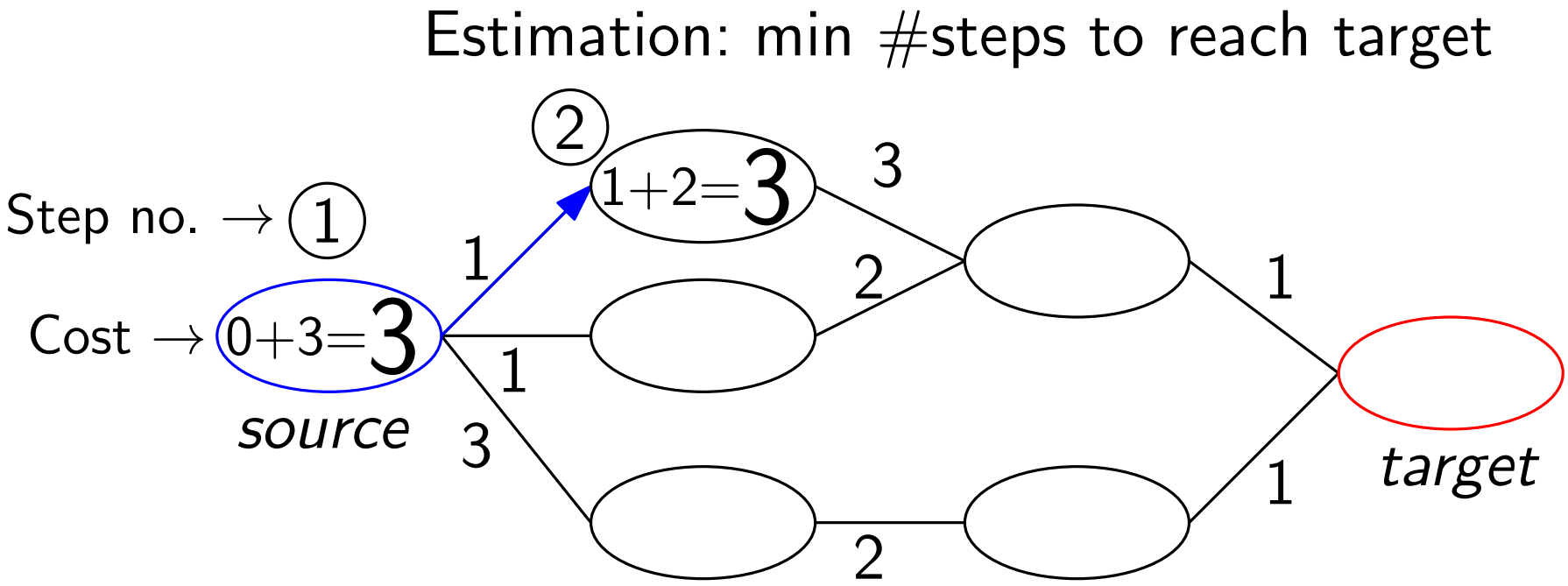

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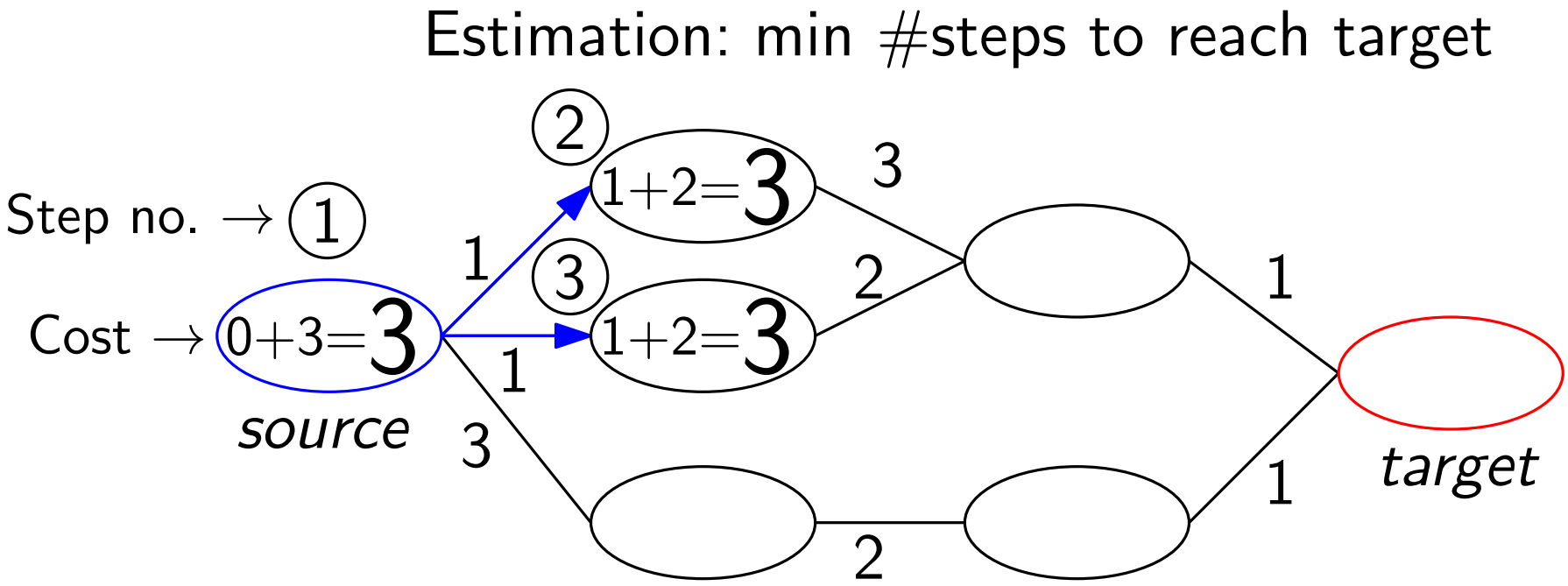

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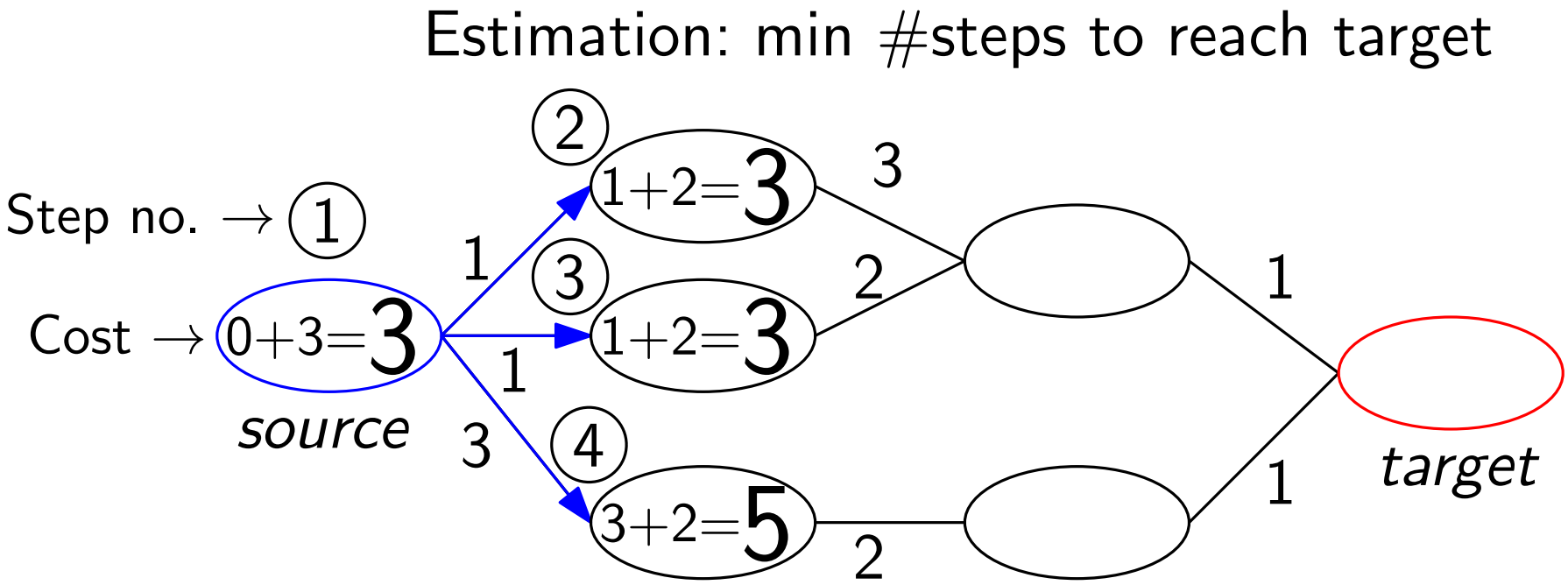

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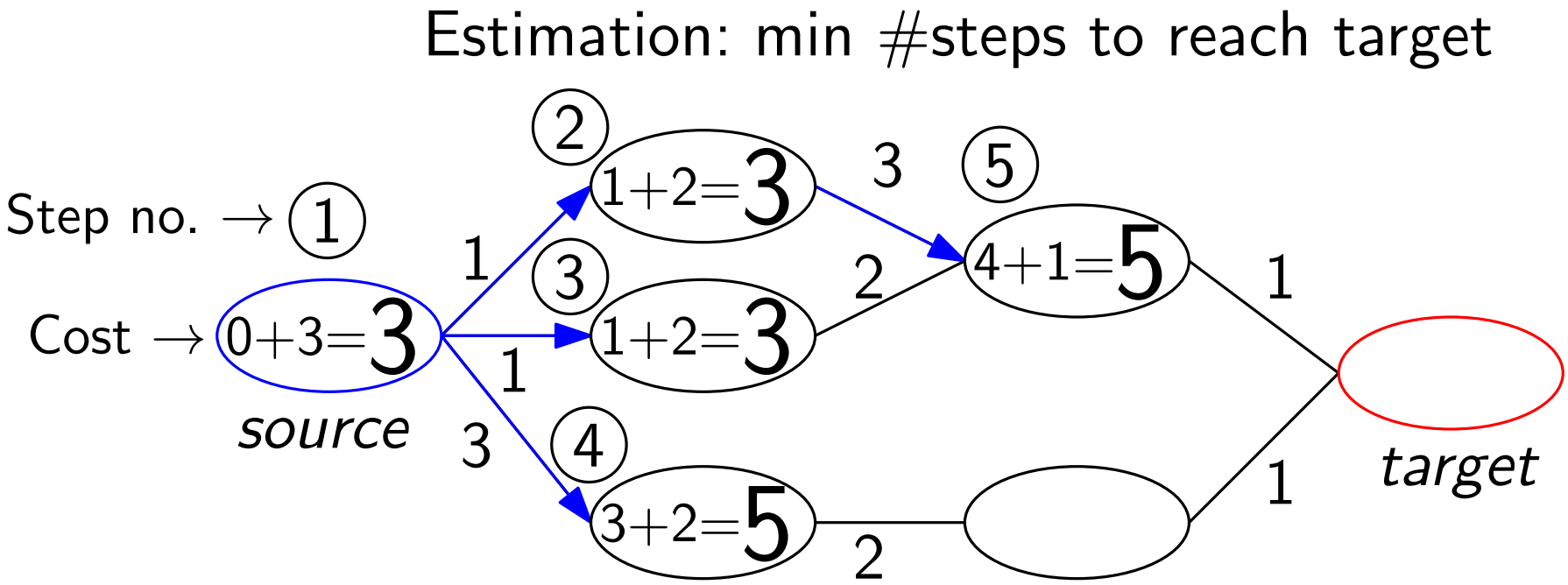

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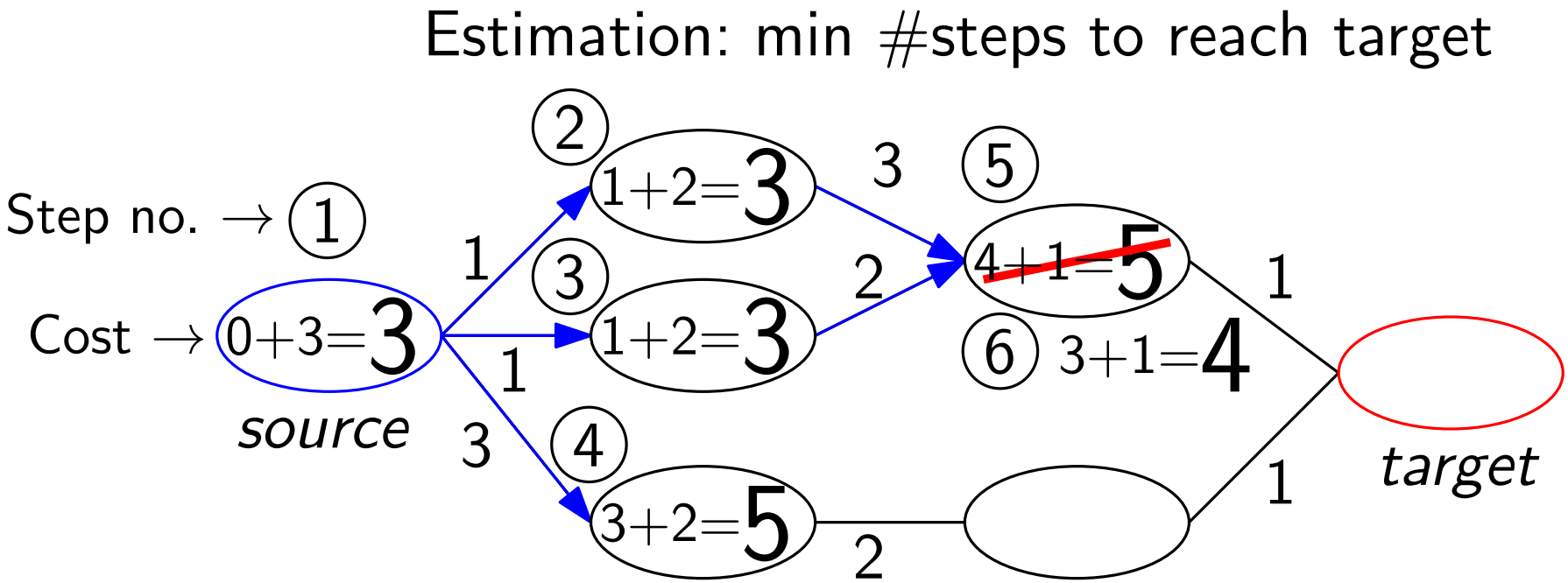

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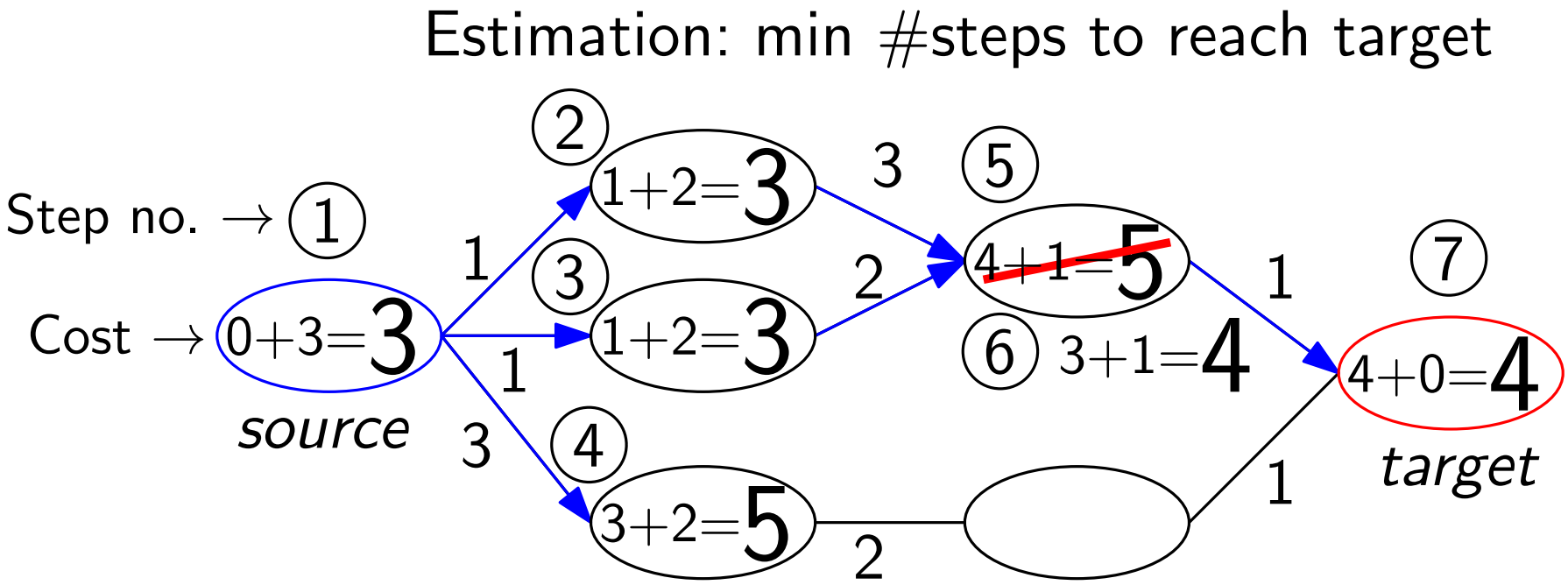
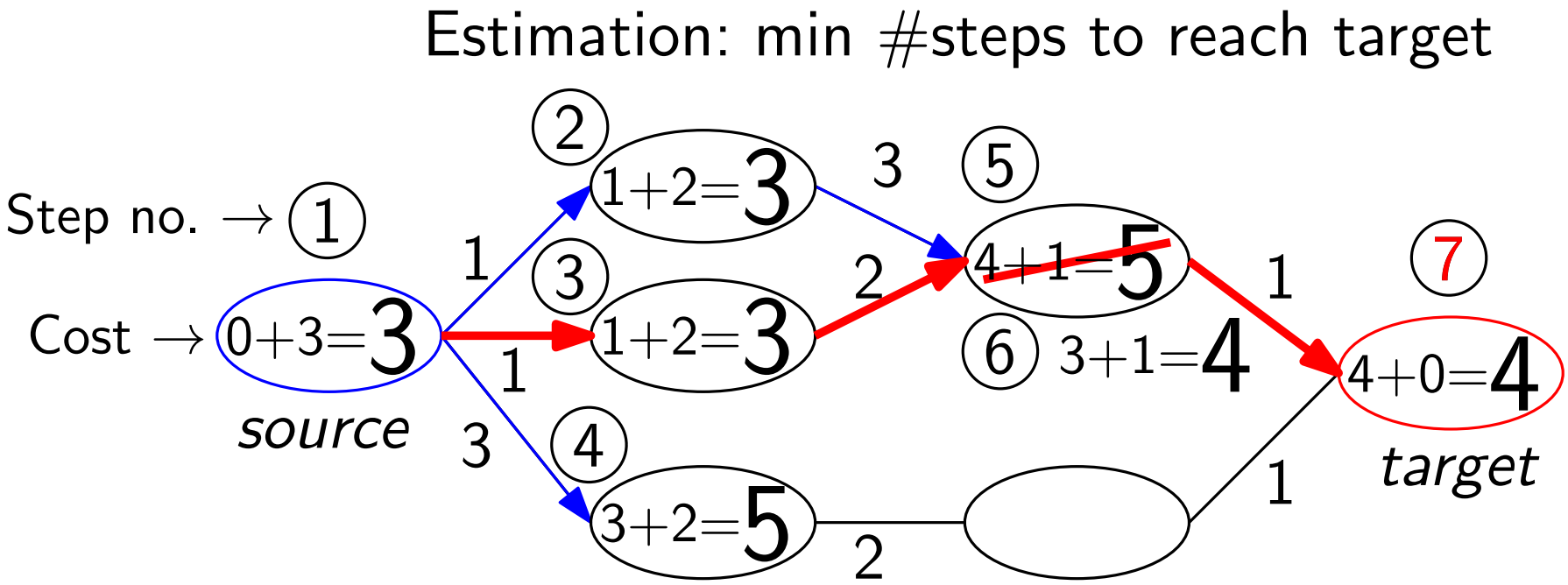
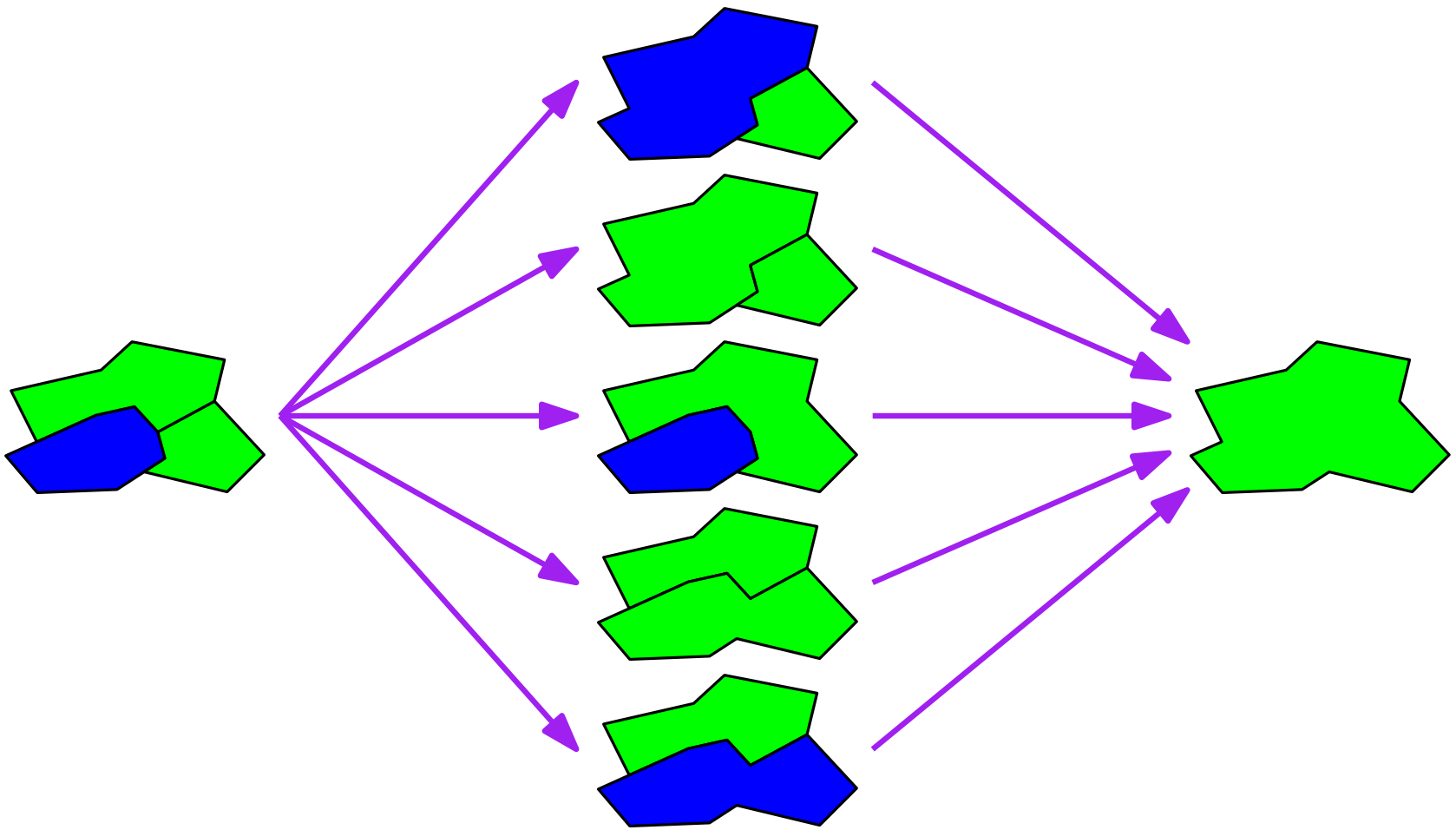

Estimation: min #steps to reach target
Step no. → 1
Cost → 0+3=3
source
2
1+2=3
3
1+2=3
4
3+2=5
5
4+1=5
6
3+1=4
7
4+0=4
target
1
1
3
3
2
2
1
1

A* Algorithm

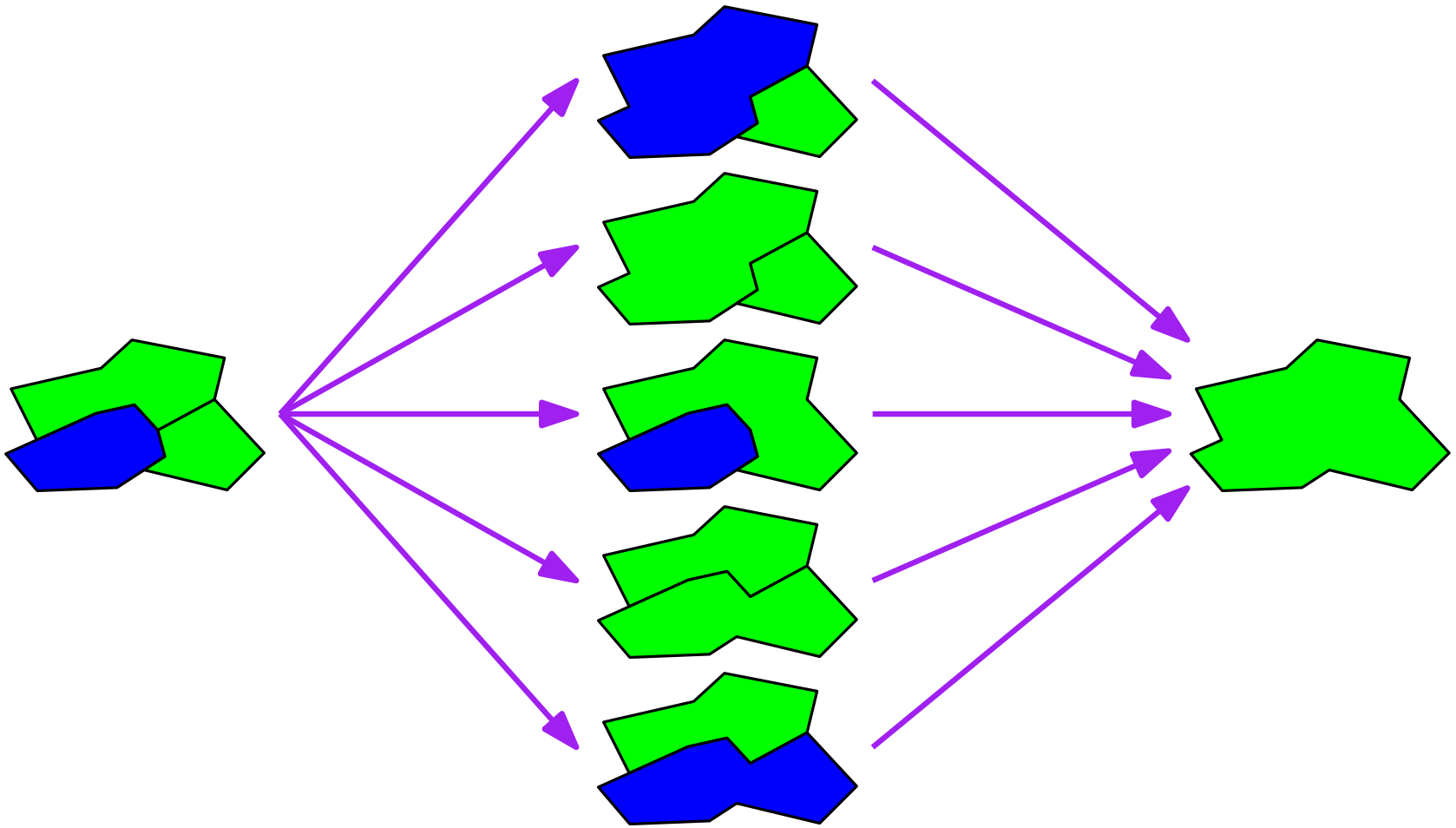


Formalizing a Pathfinding



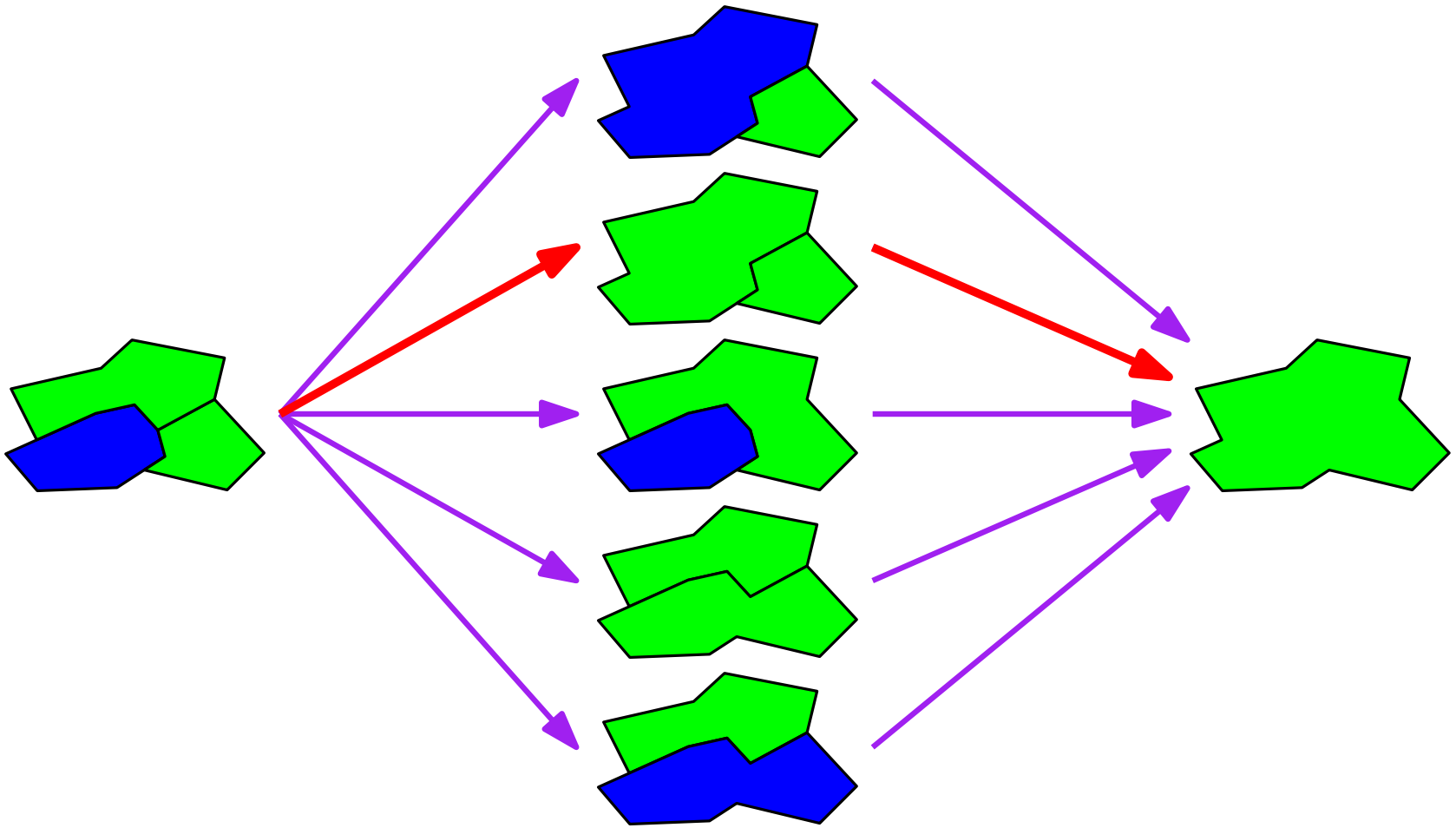
Formalizing a Pathfinding

- Each subdivision is represented as a node



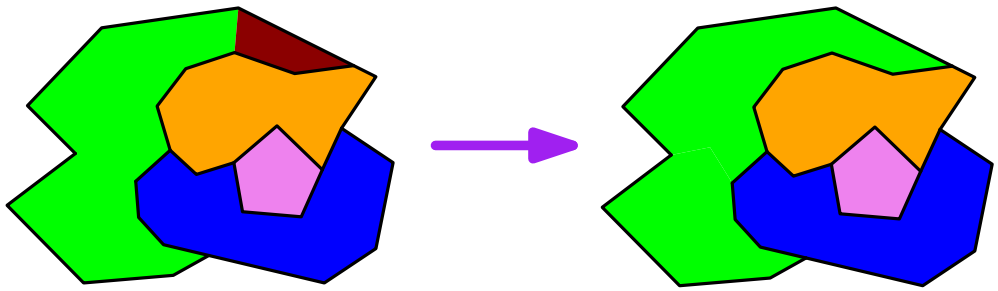
Formalizing a Pathfinding

- Each subdivision is represented as a node
- Find a shortest path with respect to cost functions



Cost Function

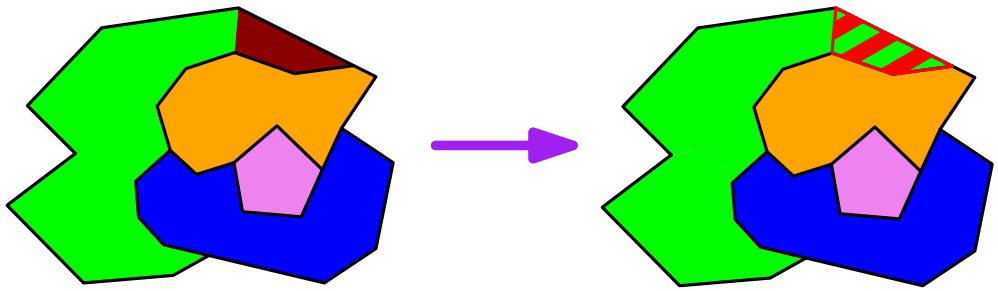
- Type change
  $f_{\text{type}}(\mathcal{P}_{s-1,i}, \mathcal{P}_{s,j}) =$



Cost Function

- Type change

$$f_{\text{type}}(\mathcal{P}_{s-1,i}, \mathcal{P}_{s,j}) = \frac{A_p}{A_R} \cdot \frac{Cost(T(p), T(q))}{T_{\max}}$$



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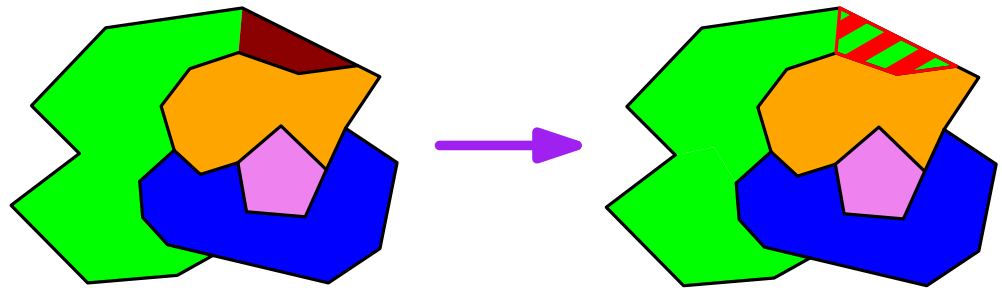
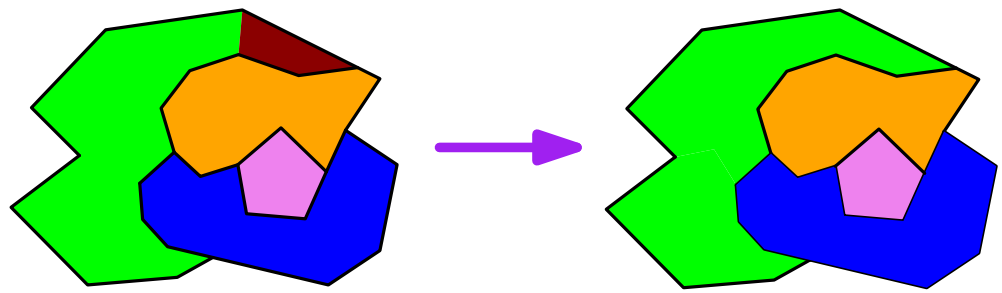


- Shape (non-compactness)

$$f_{\text{shape}}(\mathcal{P}_{s,k}) =$$



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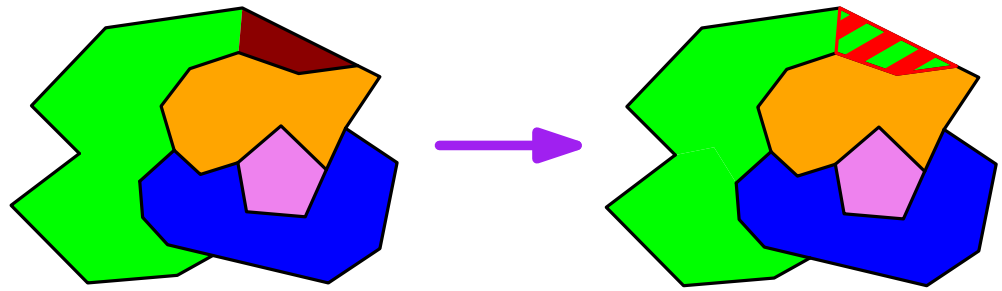
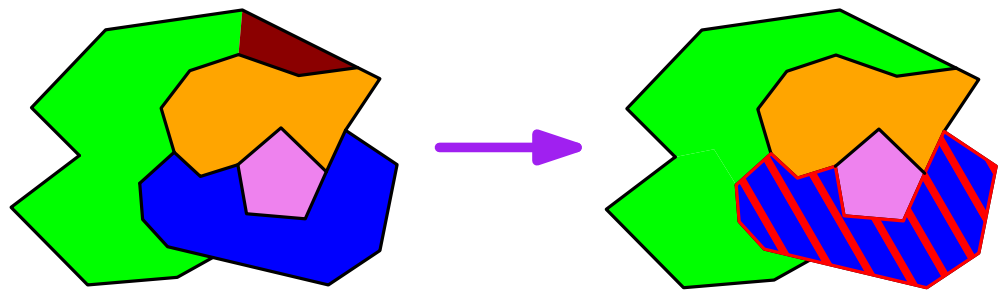
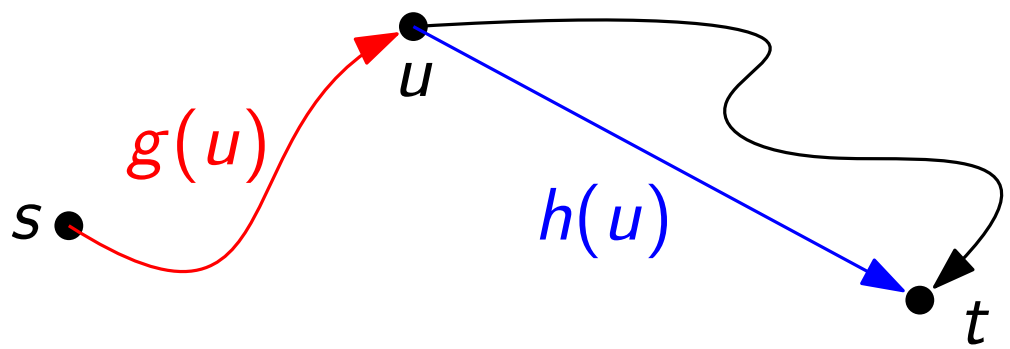


- Shape (non-compactness)

$$f_{\text{shape}}(\mathcal{P}_{s,k}) = \frac{1 - \min_{p \in \mathcal{P}_{s,k}} c_p}{n-2}$$

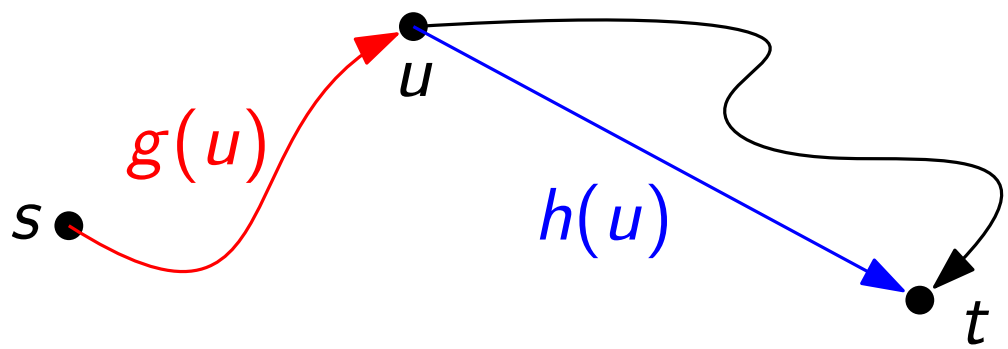


Exact Cost and Estimated Cost



Exact Cost and Estimated Cost

- *Exact cost*
  $g(\mathcal{P}_{t,i}) = (1-\lambda)\sum_{j=2}^{t} f_{\text{type}}(\mathcal{P}_{j-1,i_{j-1}}, \mathcal{P}_{j,i_j}) + \lambda \sum_{j=2}^{t-1} f_{\text{shape}}(\mathcal{P}_{j,i_j})$



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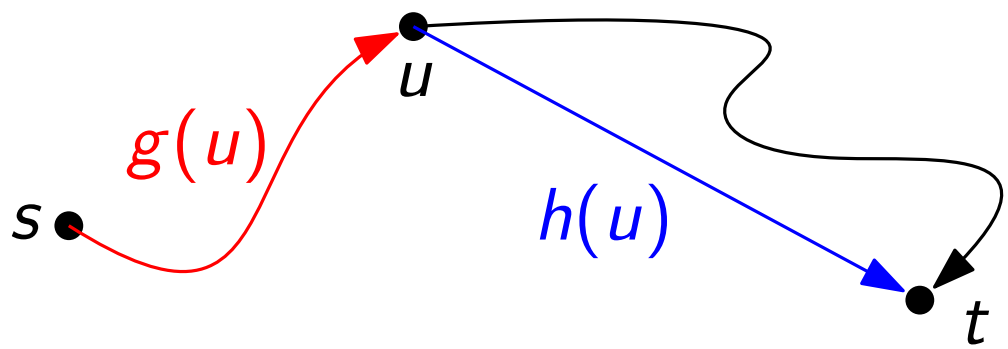
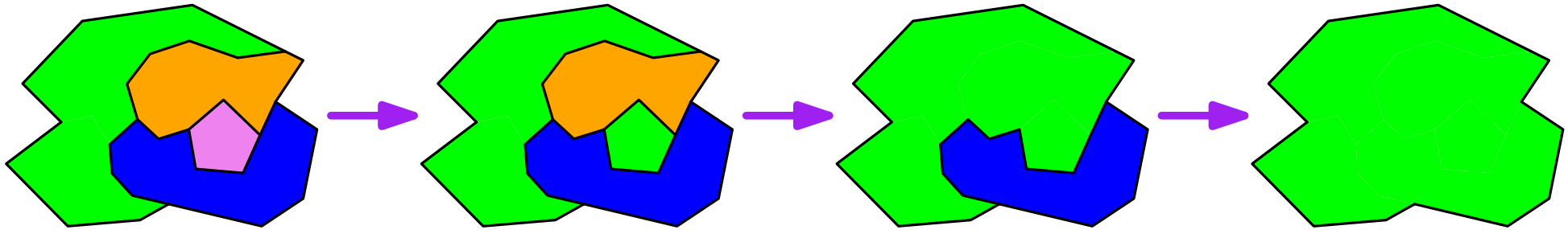
- Estimated cost
  $h(\mathcal{P}_{t,i}) = (1-\lambda) h_{\text{type}}(\mathcal{P}_{t,i}) + \lambda h_{\text{shape}}(\mathcal{P}_{t,i})$



Estimated Cost

- $h_{\text{type}}(\mathcal{P}_{t,i}) = \sum_{s=t}^{n-1} f_{\text{type}}(\mathcal{P}_{s,i_s}, \mathcal{P}_{s+1,i_{s+1}})$.
  We assume: Each patch immediately gets the target type.



$t = 2$ $t = 3$ $t = 4$ $t = 5$

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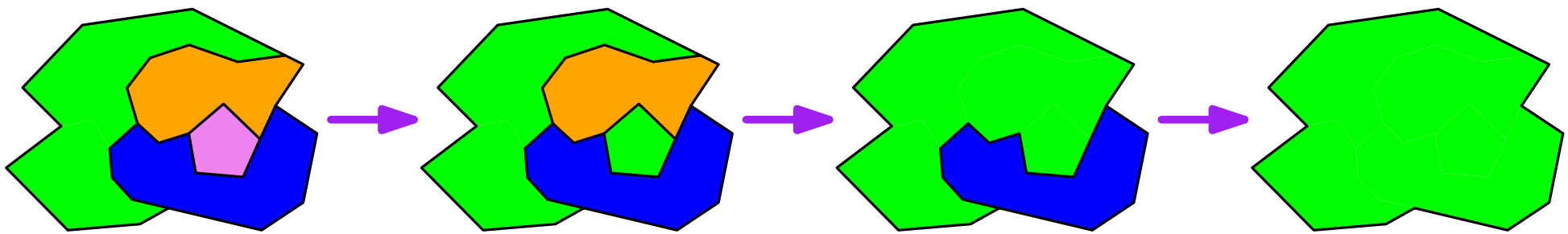
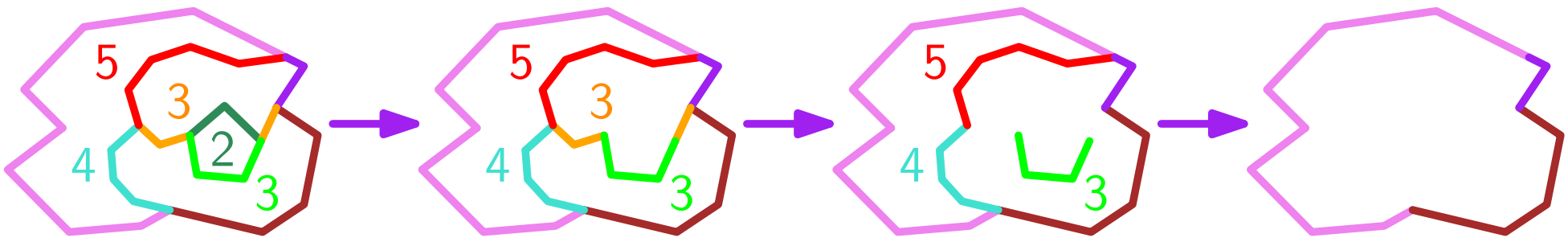


$t = 2$ $t = 3$ $t = 4$ $t = 5$

- $h_{\text{shape}}(\mathcal{P}_{t,i}) = \sum_{s=t}^{n-1} C(\mathcal{P}_{s,j_s})$,
  The more the edges remain, the smaller the estimated compactness $C(\mathcal{P}_{s,j_s})$ is
  We assume: The boundary with the fewest edges is removed.



$n_{\text{int}}(\mathcal{P}_{2,j_2}) = 17$ $n_{\text{int}}(\mathcal{P}_{3,j_3}) = 15$ $n_{\text{int}}(\mathcal{P}_{4,j_4}) = 12$ $n_{\text{int}}(\mathcal{P}_{5,j_5}) = 0$

Overestimation

- Try finding a path by exploring M nodes. If we do not find one, then we overestimate and try exploring M nodes again.
- Overestimate by increasing $k \in \{0, 1, \dots\}$:
  $F(\mathcal{P}_{t,i}) = g(\mathcal{P}_{t,i}) + 2^k h(\mathcal{P}_{t,i})$

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  With a larger k, a path seems more expensive (or longer), thus may not be explored

Not optimal anymore if $k > 0$!

Outline

- Introduction
- Methodology
- Case Study
- Concluding Remarks

Case Study

Environment

- C# (using the .NET Framework 4.0)
- ArcObjects SDK 10.2
- Windows 7, 3.3 GHz dual core CPU, 8 GB RAM
- Time measure: Stopwatch (a class in C#)

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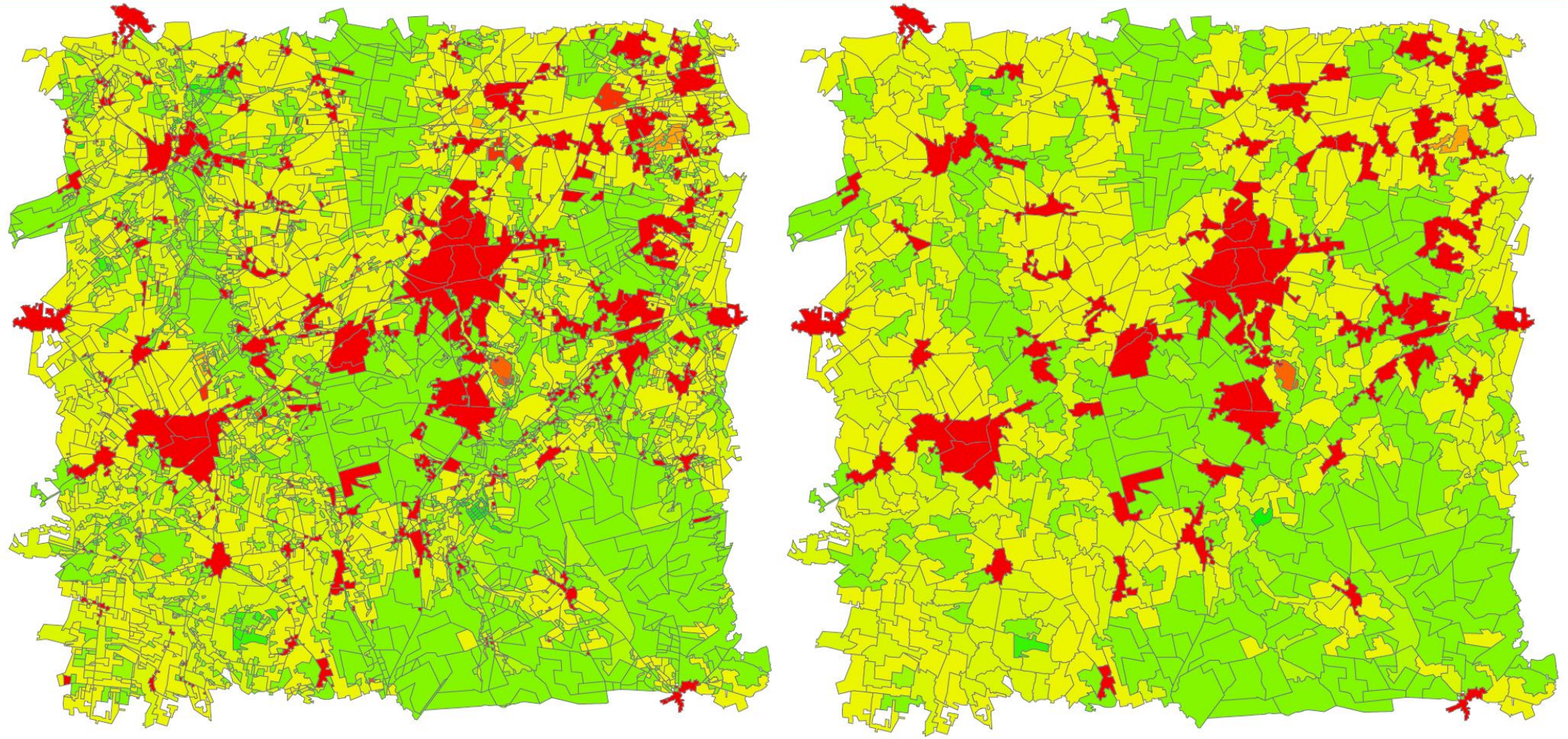
Data

- Source: scale 1 : 50,000; 5,448 patches; place "Buchholz in der Nordheide"; from ATKIS (Das Amtliche Topographisch-Kartographische Informationssystem), processed by Haunert (2009, pp. 61–66)
- Target: scale 1 : 250,000; 730 patches; generalized from the source by Haunert and Wolff (2010)

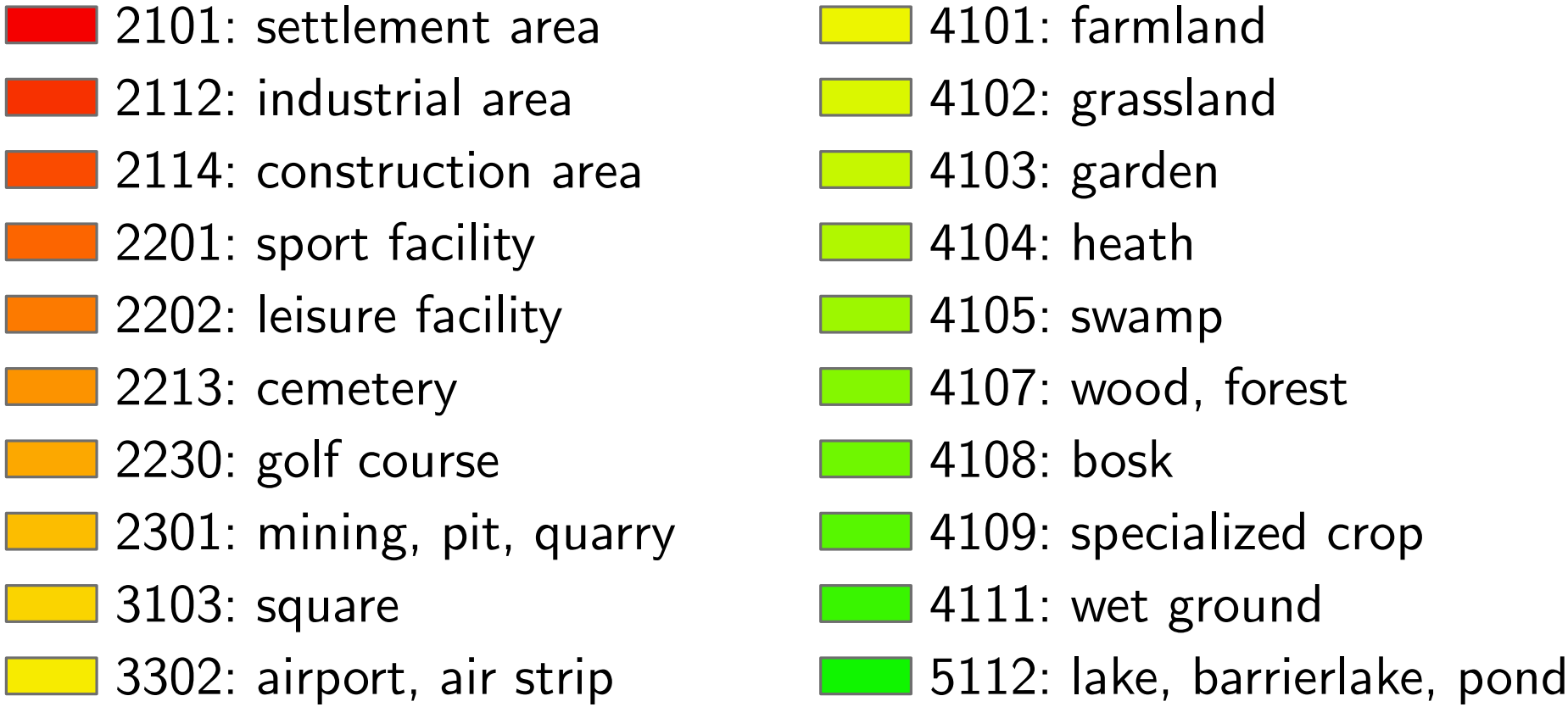
Data



5,448 patches, scale 1 : 50,000

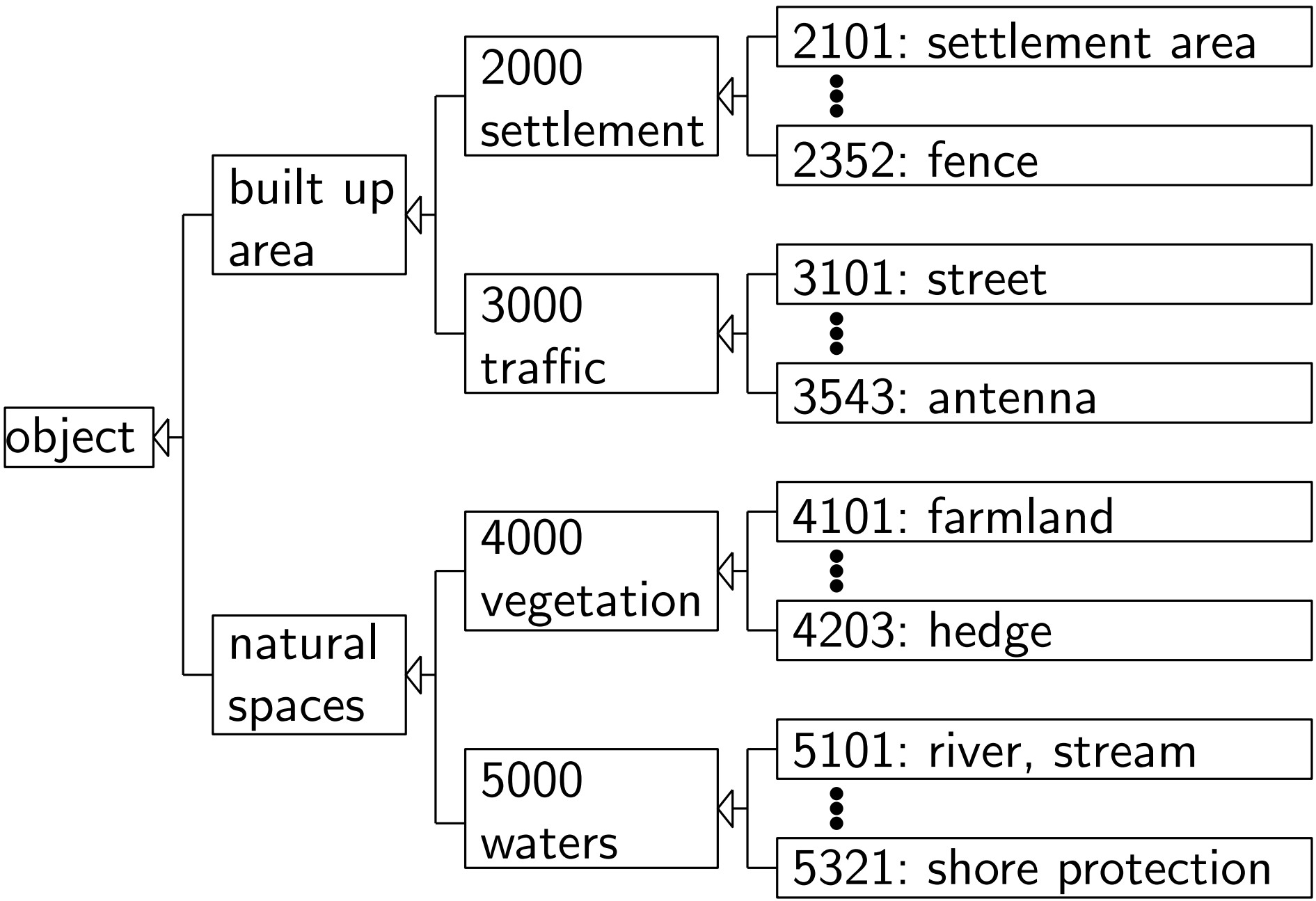
730 patches, scale 1 : 250,000

Legend



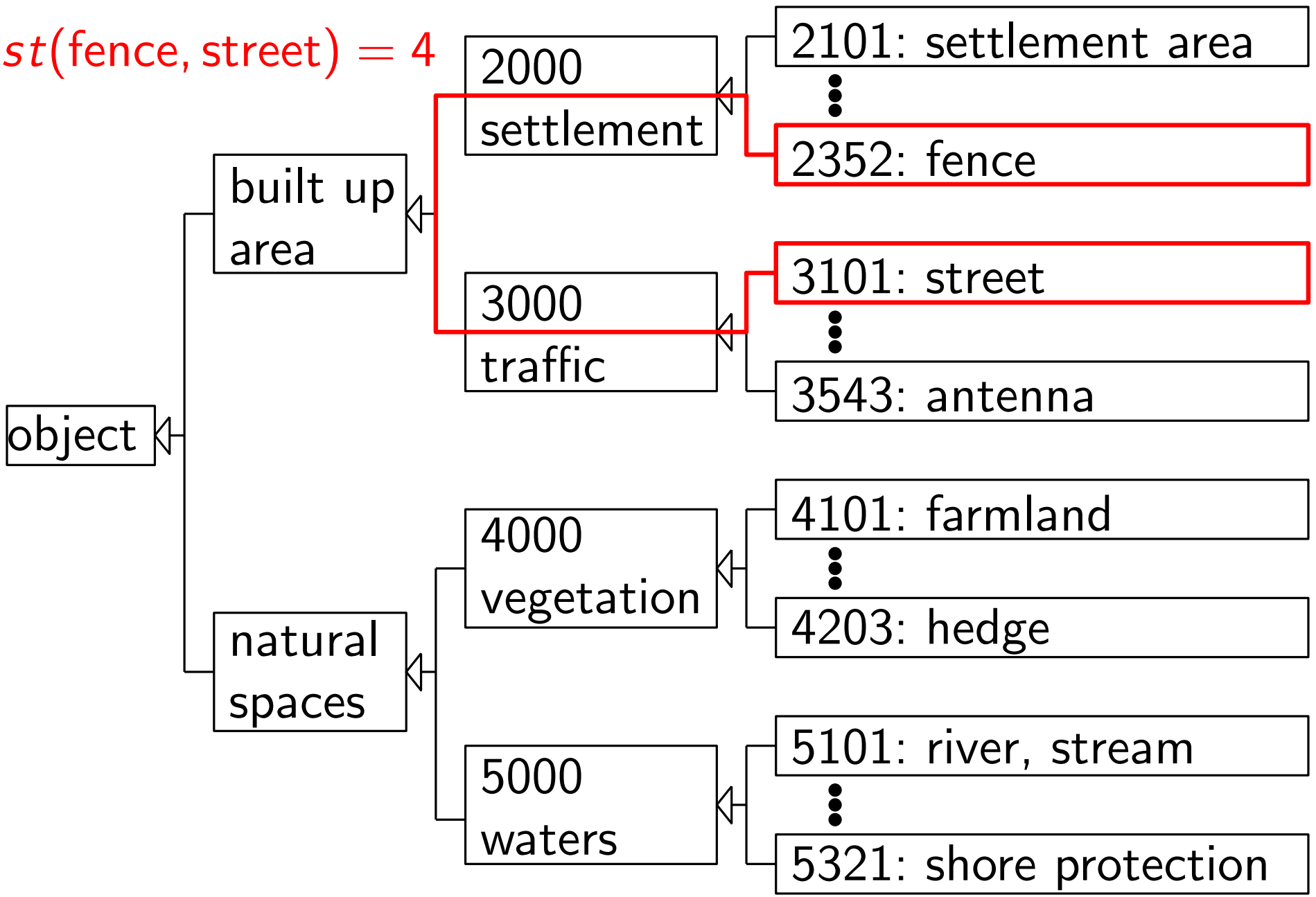
The 20 land-cover types appearing in our data

Type Distance



Type Distance

$Cost(\text{fence}, \text{street}) = 4$



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- Running time: 36 min
- Largest overestimation factor: 512

Cost in detail

ID	n	m	K_i	R_{type}	R_{shape}	Time (s)
543	20	40	512	1.000	0.516	175.7
94	32	74	64	0.016	4.577	163.6
⋮	⋮	⋮	⋮	⋮	⋮	⋮
358	21	32	1	1.000	1020.133	1.3
97	20	35	1	1.000	179.132	0.9
257	20	33	1	1.000	463.178	5.9
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Cost in detail

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257	20	33	1	1.000	463.178	5.9
⋮	⋮	⋮	⋮	⋮	⋮	⋮

$R_{\text{type}} = g_{\text{type}}(\mathcal{P}_{\text{goal}})/h_{\text{type}}(\mathcal{P}_{\text{start}})$

Good estimation for type change

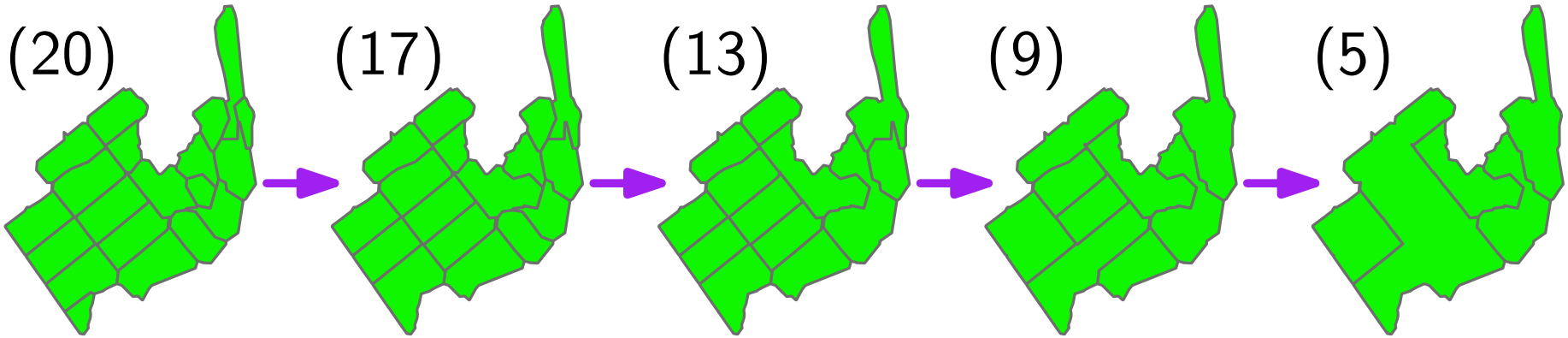
Cost in detail

ID	n	m	K_i	R_{type}	R_{shape}	Time (s)
543	20	40	512	1.000	0.516	175.7
94	32	74	64	0.016	4.577	163.6
⋮	⋮	⋮	⋮	⋮	⋮	⋮
358	21	32	1	1.000	1020.133	1.3
97	20	35	1	1.000	179.132	0.9
257	20	33	1	1.000	463.178	5.9
⋮	⋮	⋮	⋮	⋮	⋮	⋮

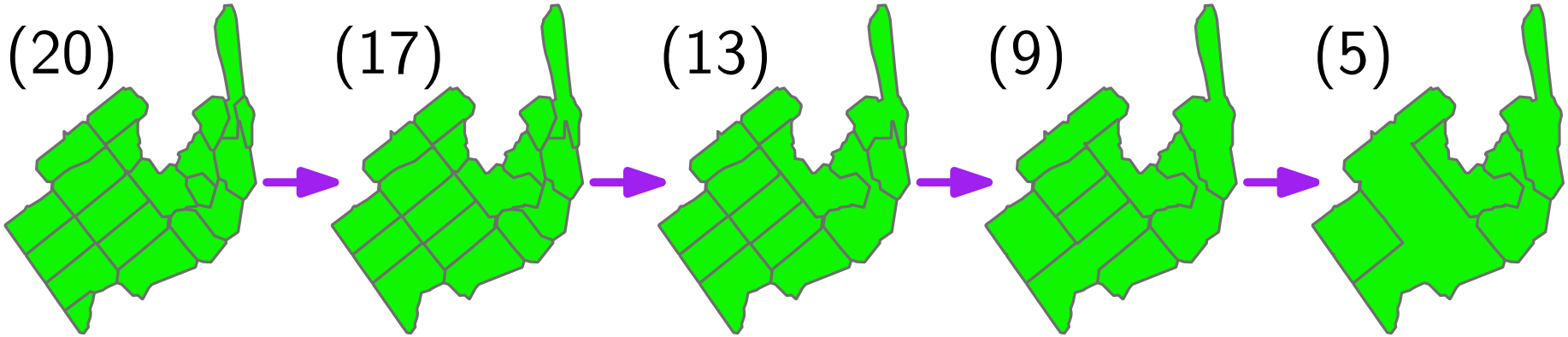
$R_{\text{type}} = g_{\text{type}}(\mathcal{P}_{\text{goal}})/h_{\text{type}}(\mathcal{P}_{\text{start}})$
Good estimation for type change

$R_{\text{shape}} = g_{\text{shape}}(\mathcal{P}_{\text{goal}})/h_{\text{shape}}(\mathcal{P}_{\text{start}})$
Poor estimation for shape (non-compactness)

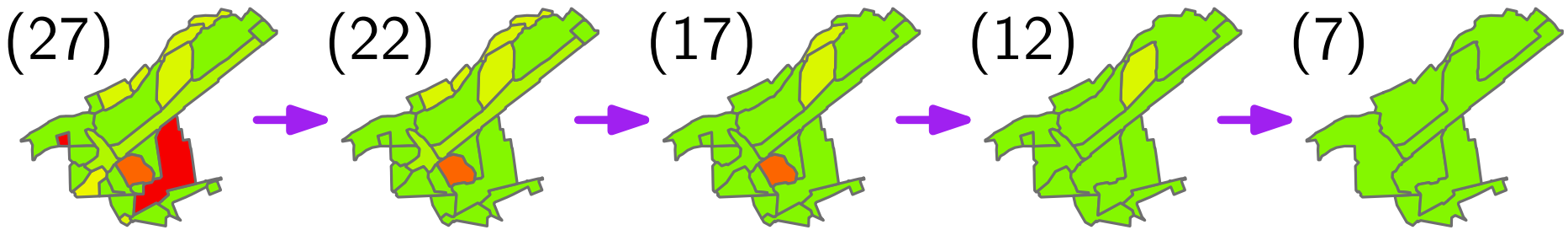
$K_{543} = 512$



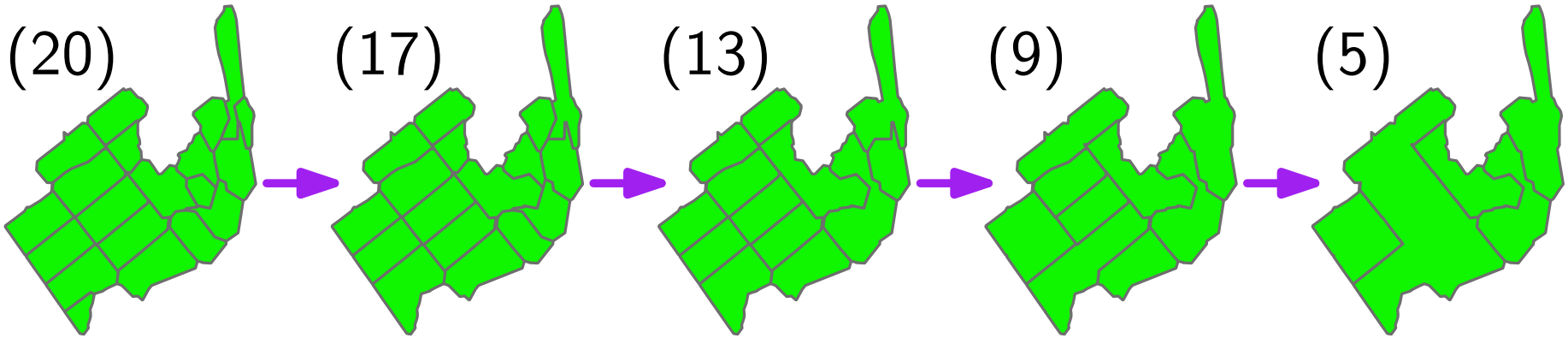
$K_{543} = 512$



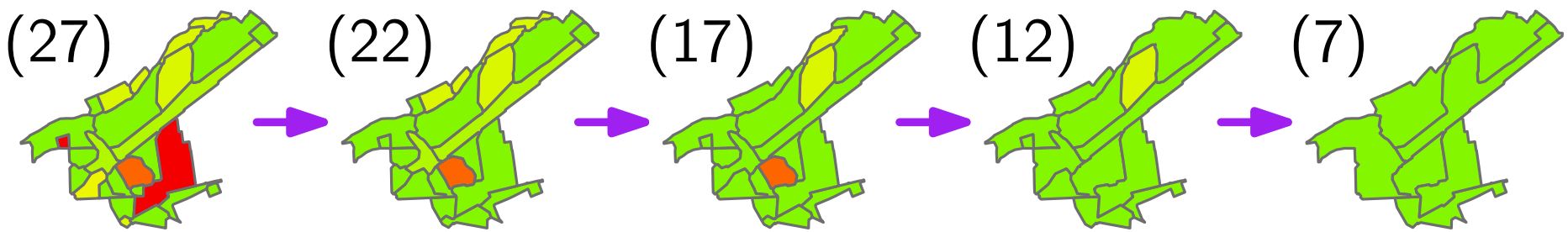
$K_{436} = 8$



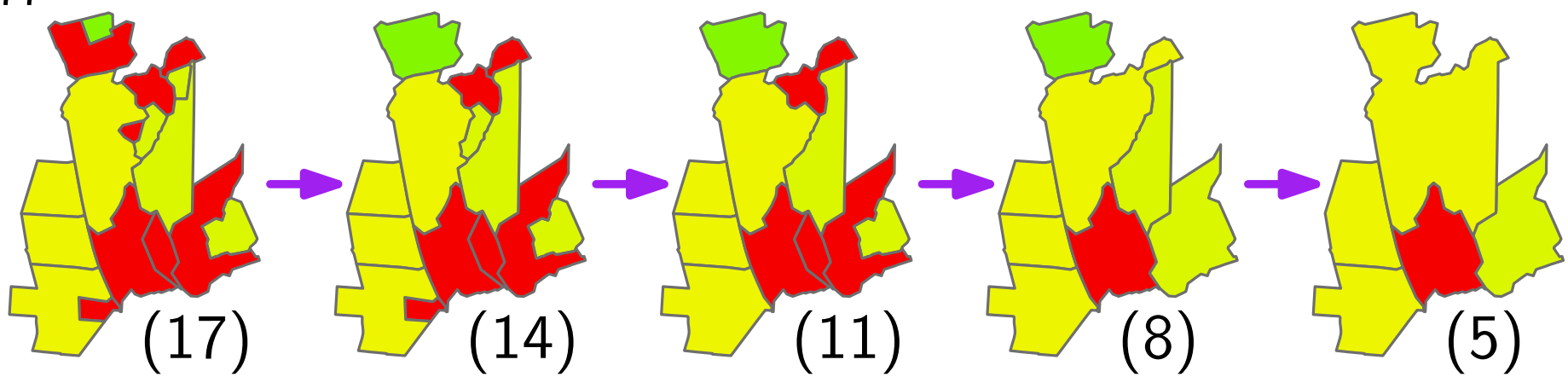
$K_{543} = 512$



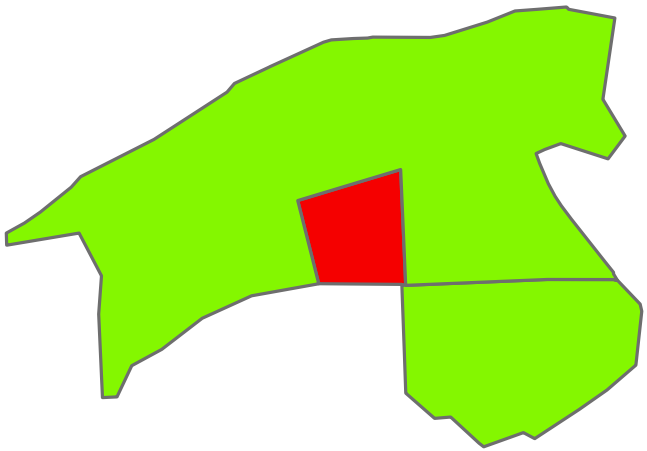
$K_{436} = 8$



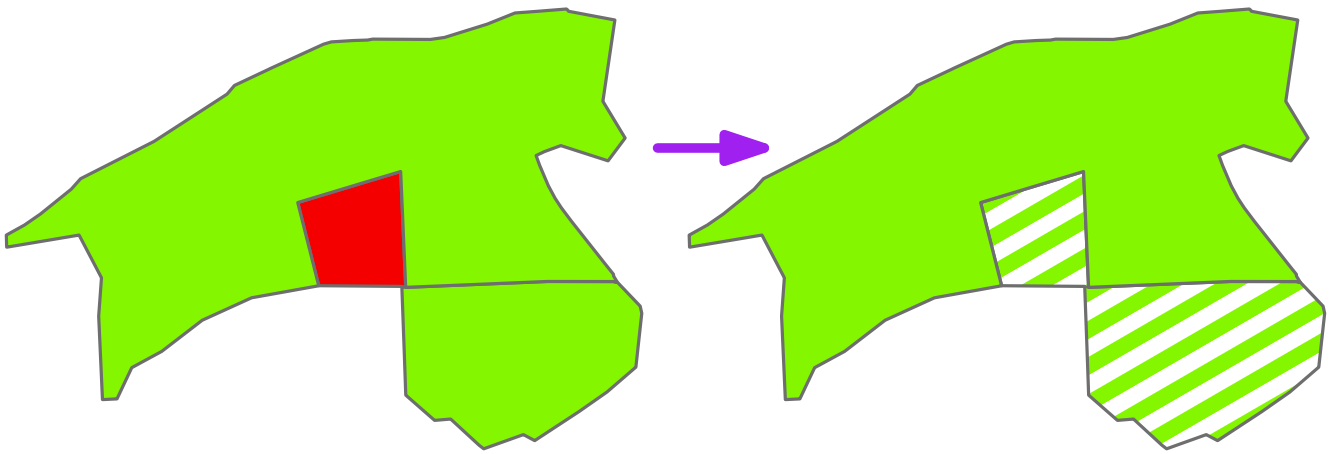
$K_{77} = 1$



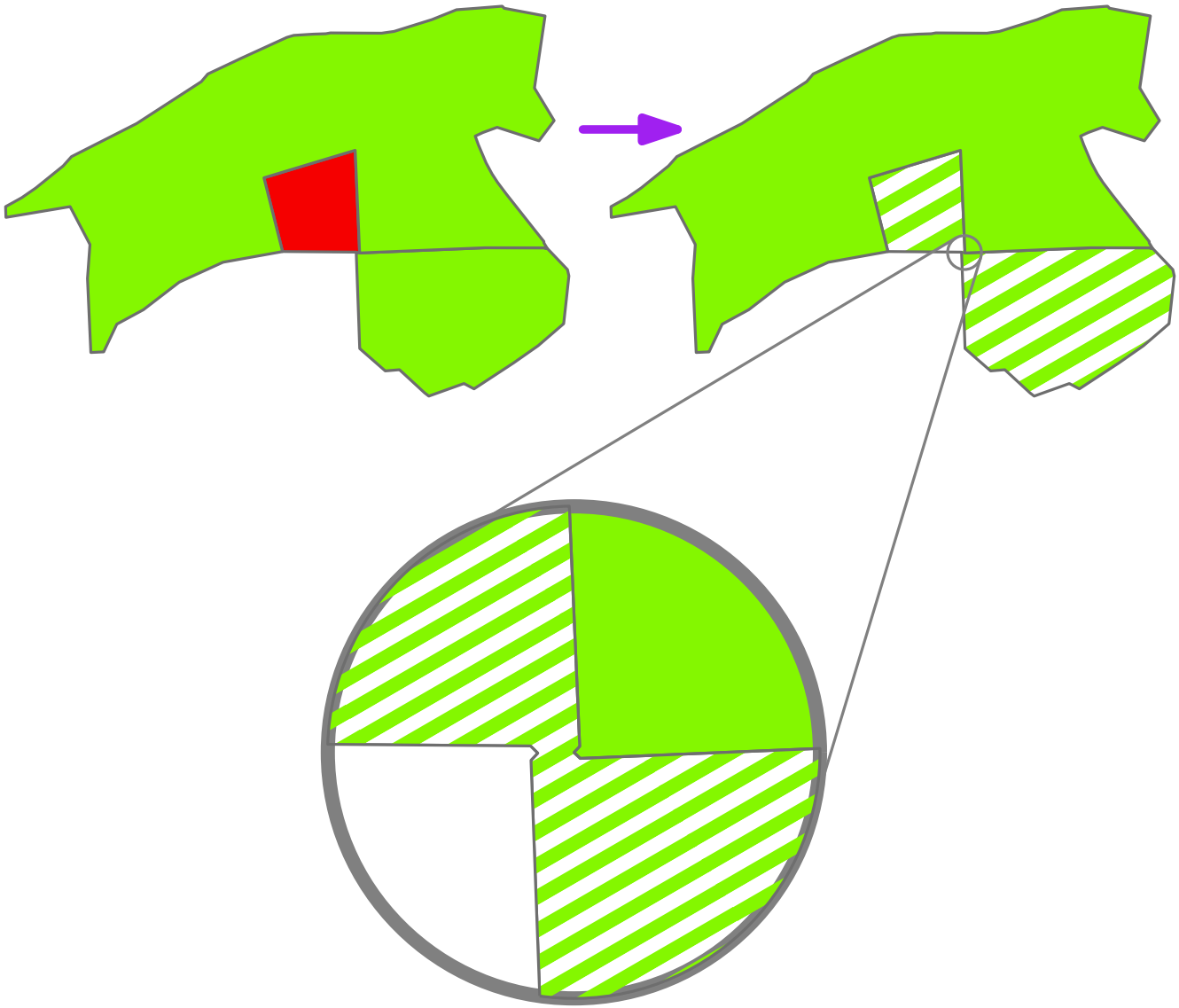
Inappropriate Step



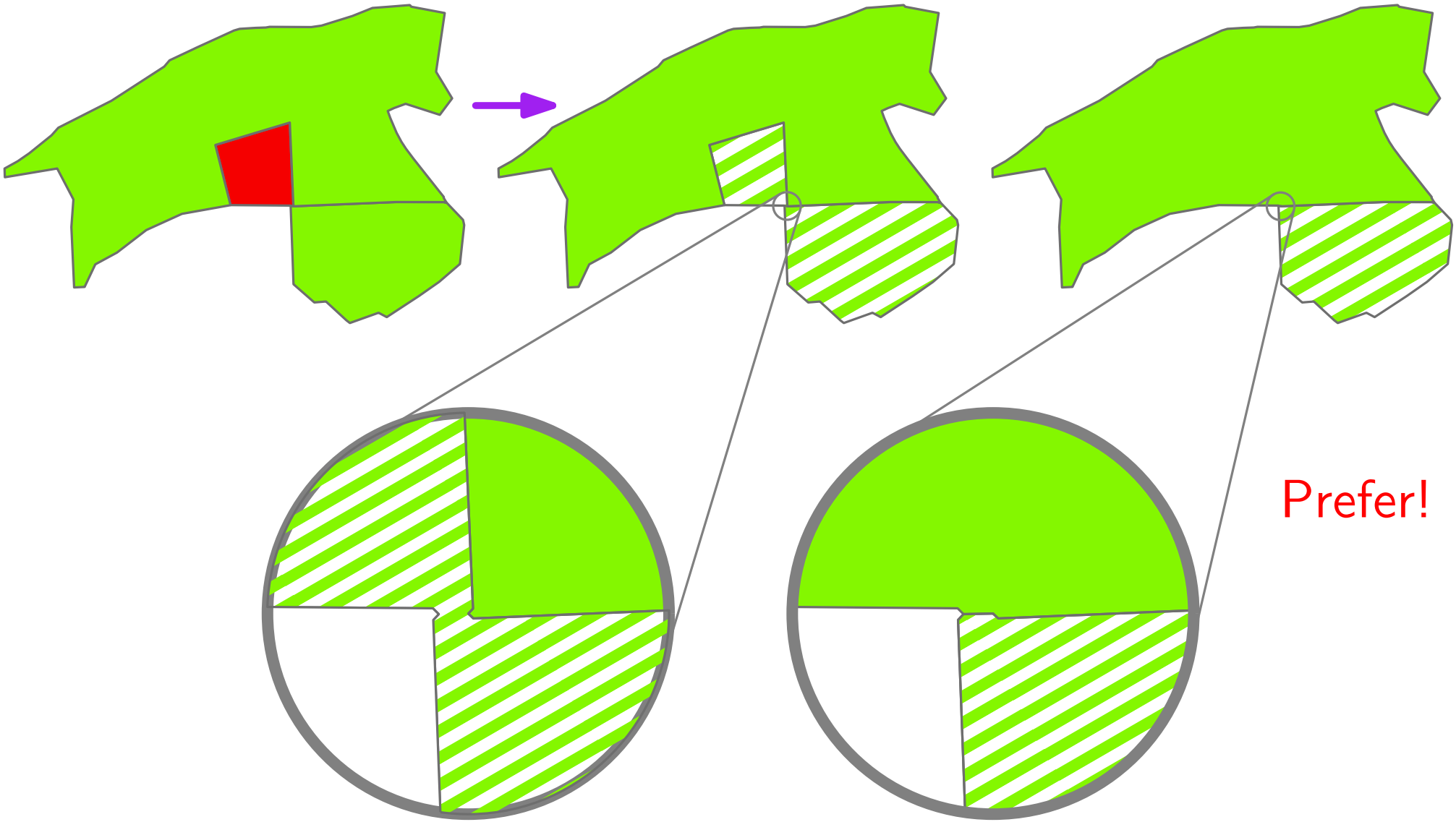
Inappropriate Step



Inappropriate Step



Inappropriate Step

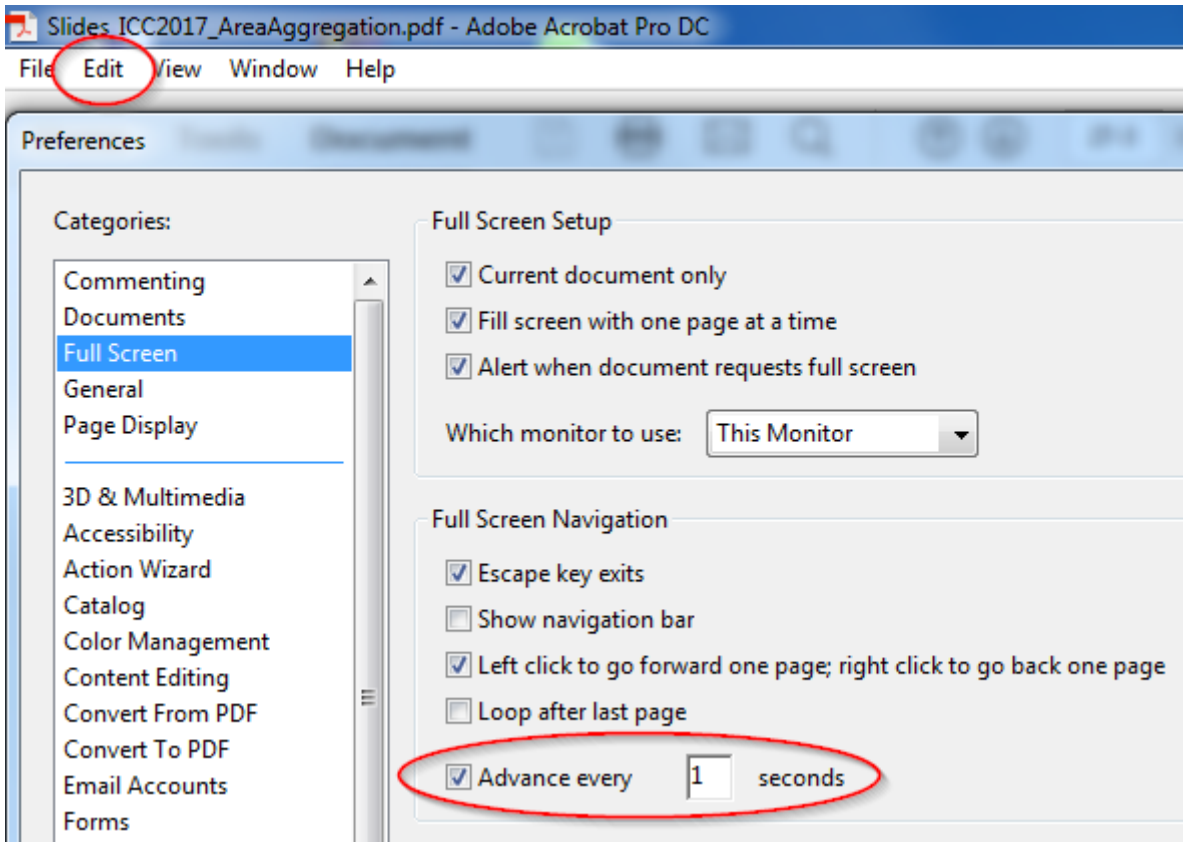


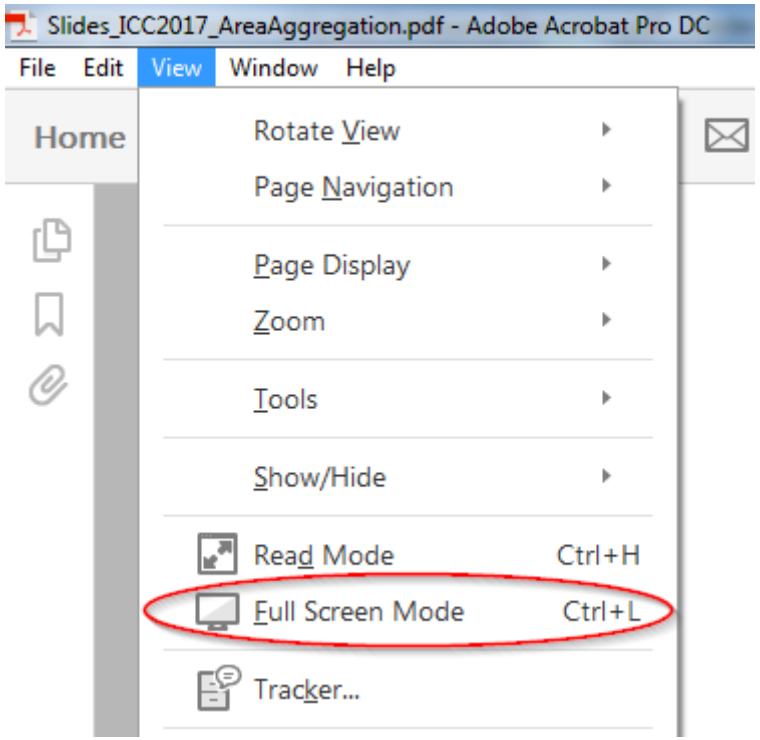
Animation

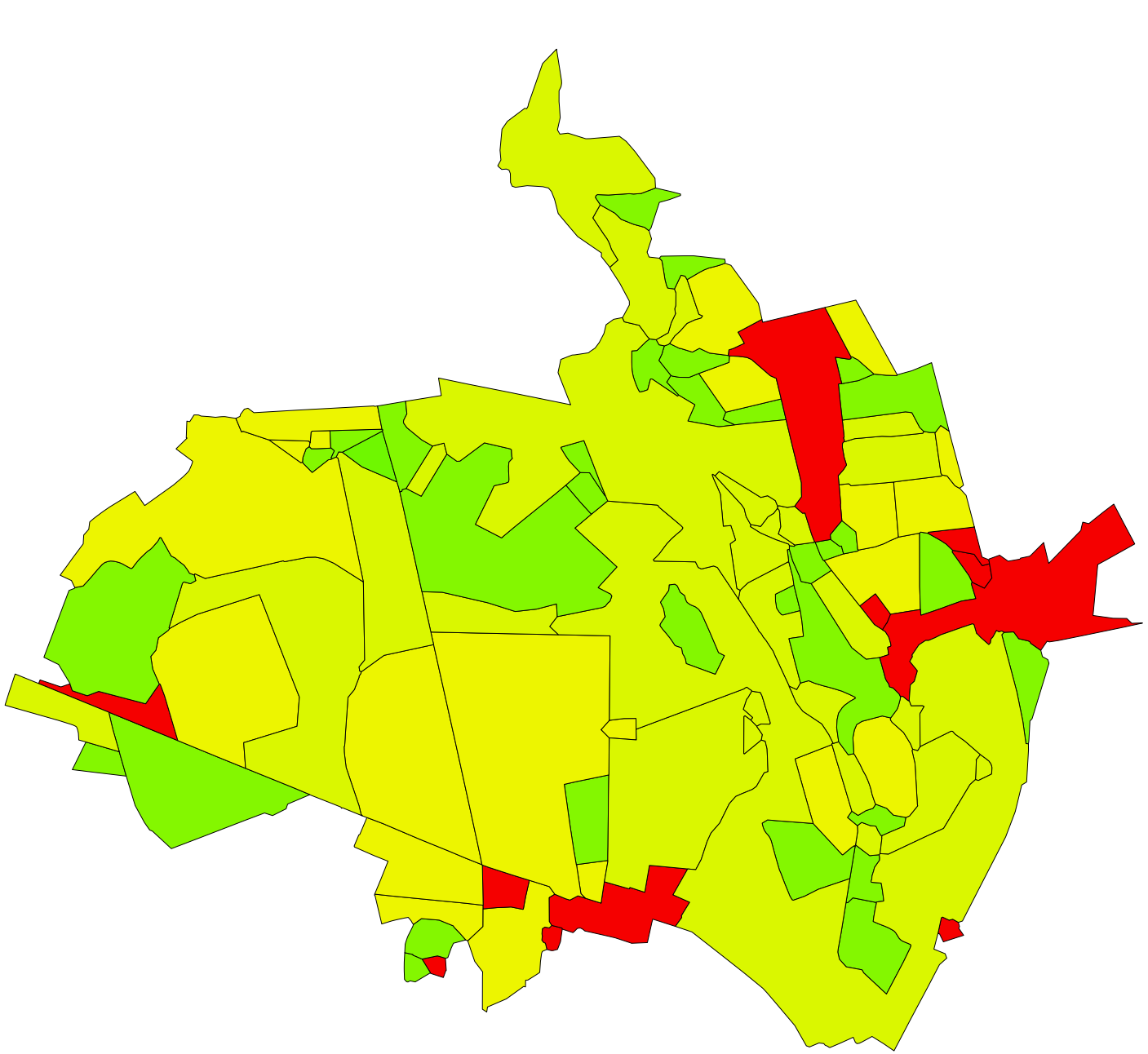
- **Thick blue polyline** represents a patch to be aggregated, and thin blue polyline represents an aggregated result.

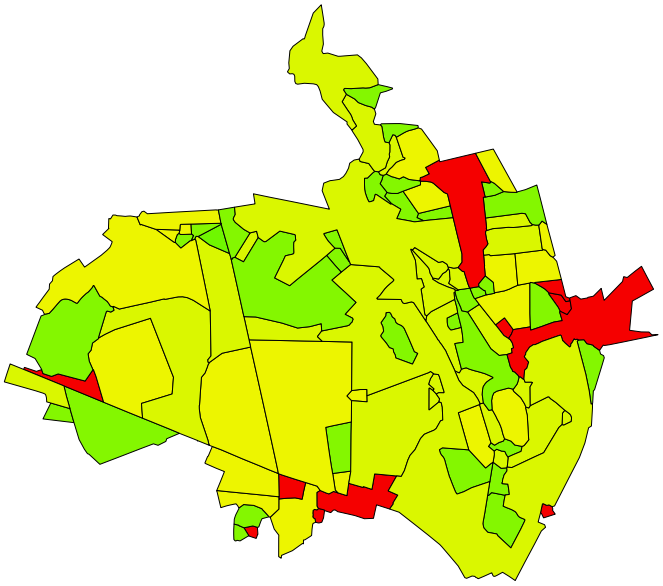
Animation

- **Thick blue polyline** represents a patch to be aggregated, and thin blue polyline represents an aggregated result.
- In Adobe Acrobat Pro, set "Advance every" to 1 second, then watch animation with "Full Screen Mode".

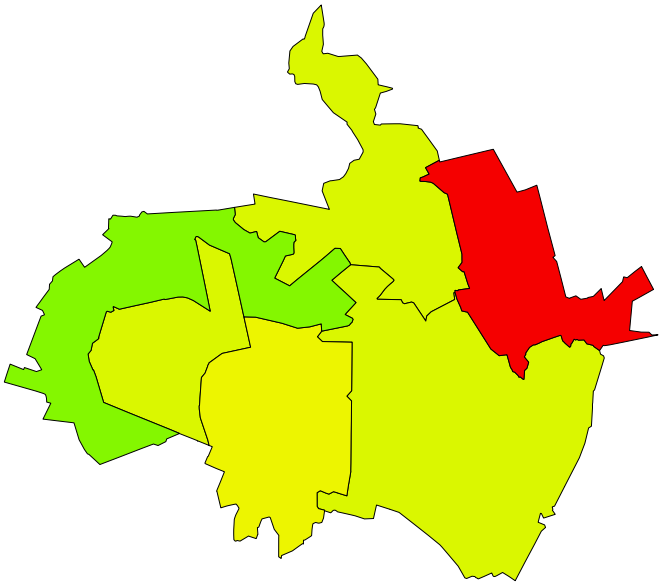




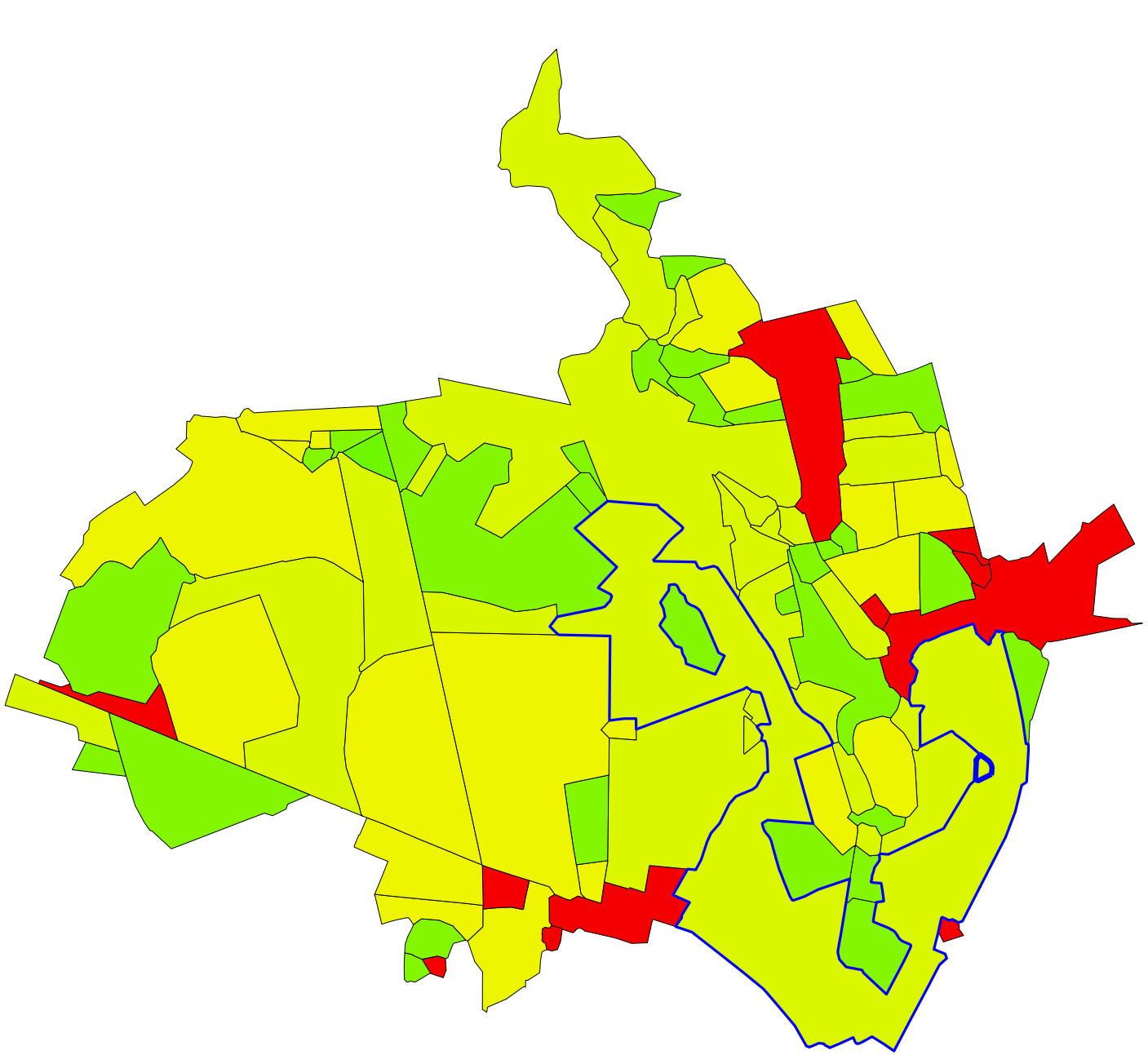


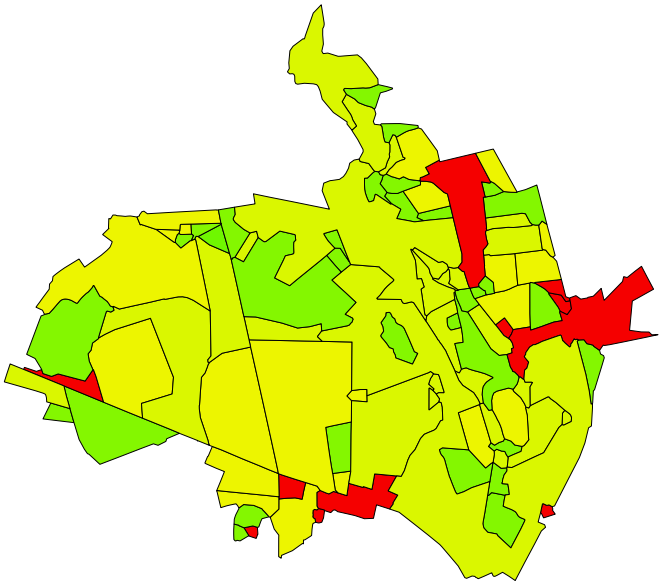


source: 92 patches

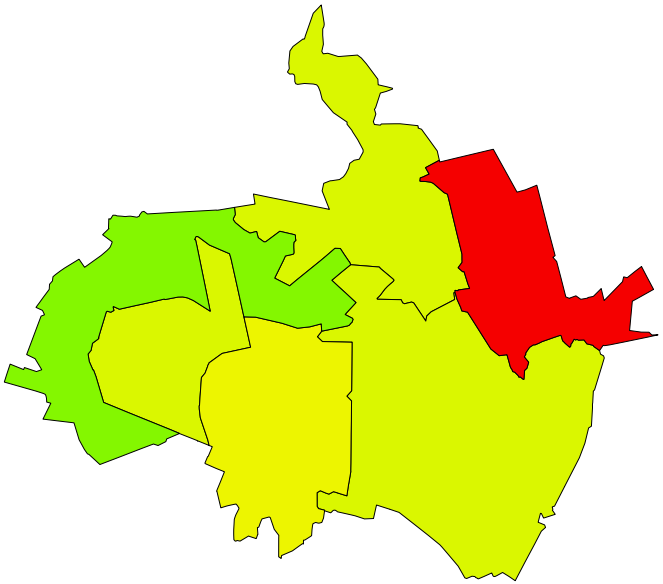


target: 6 patches

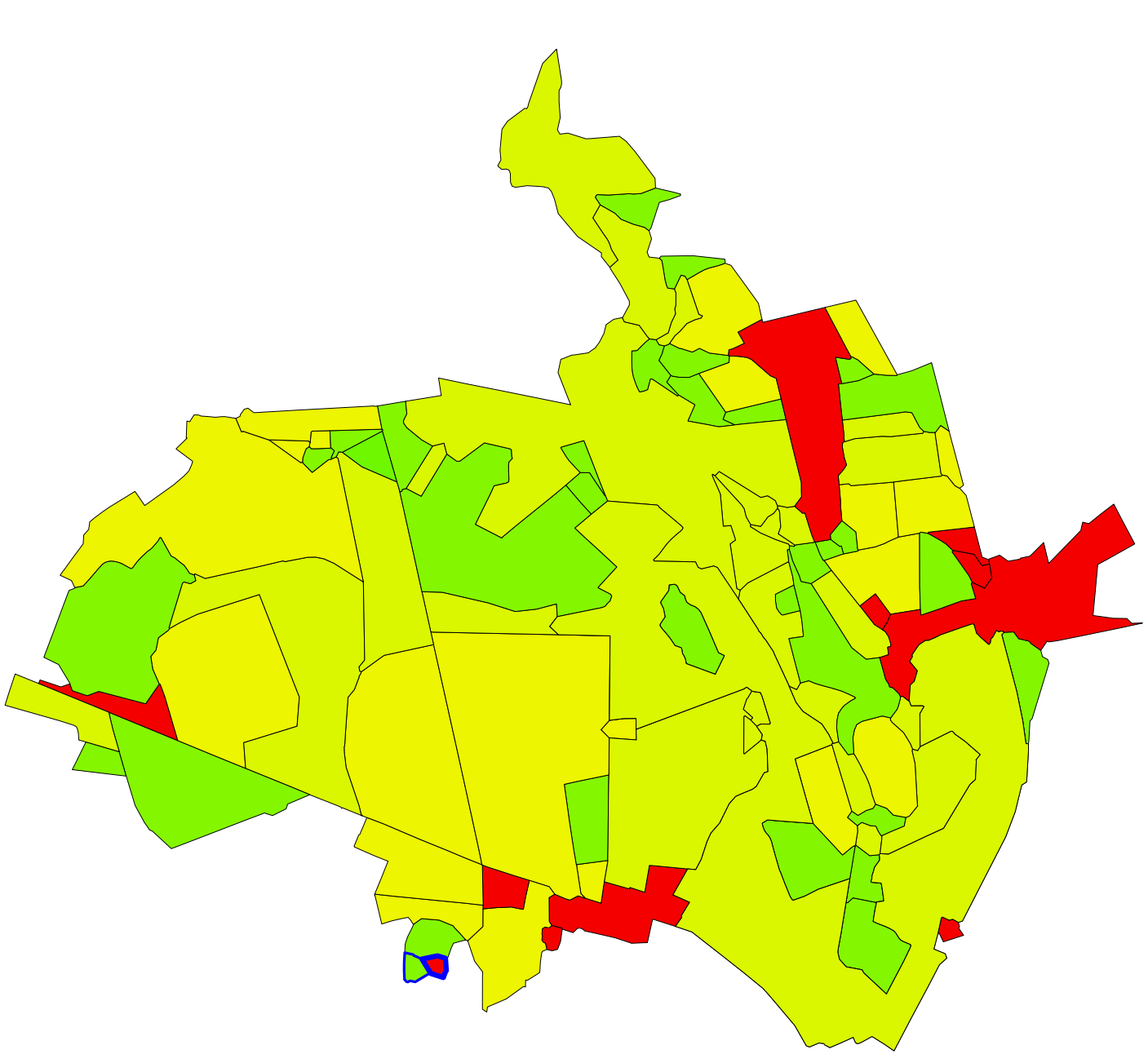


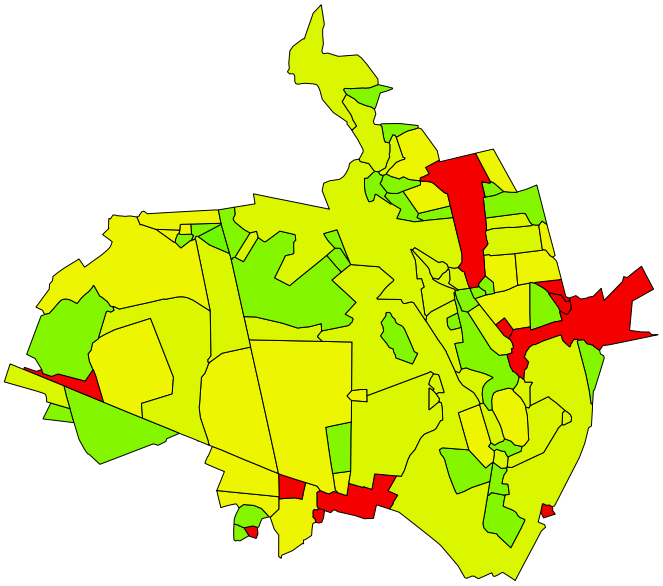


source: 92 patches

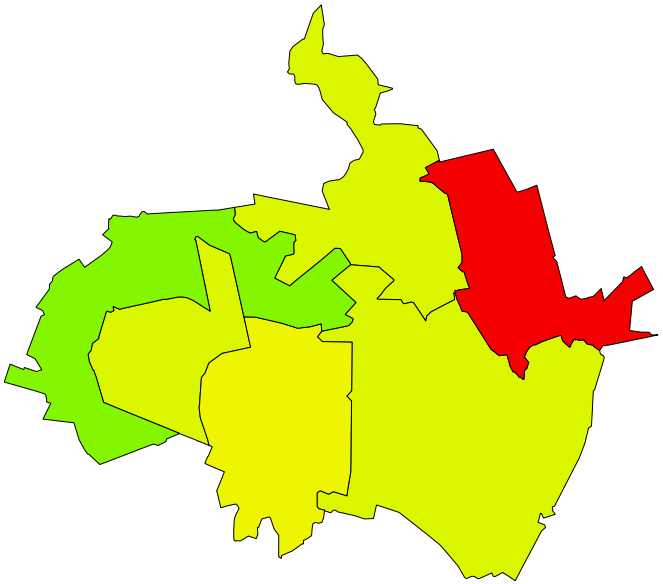


target: 6 patches

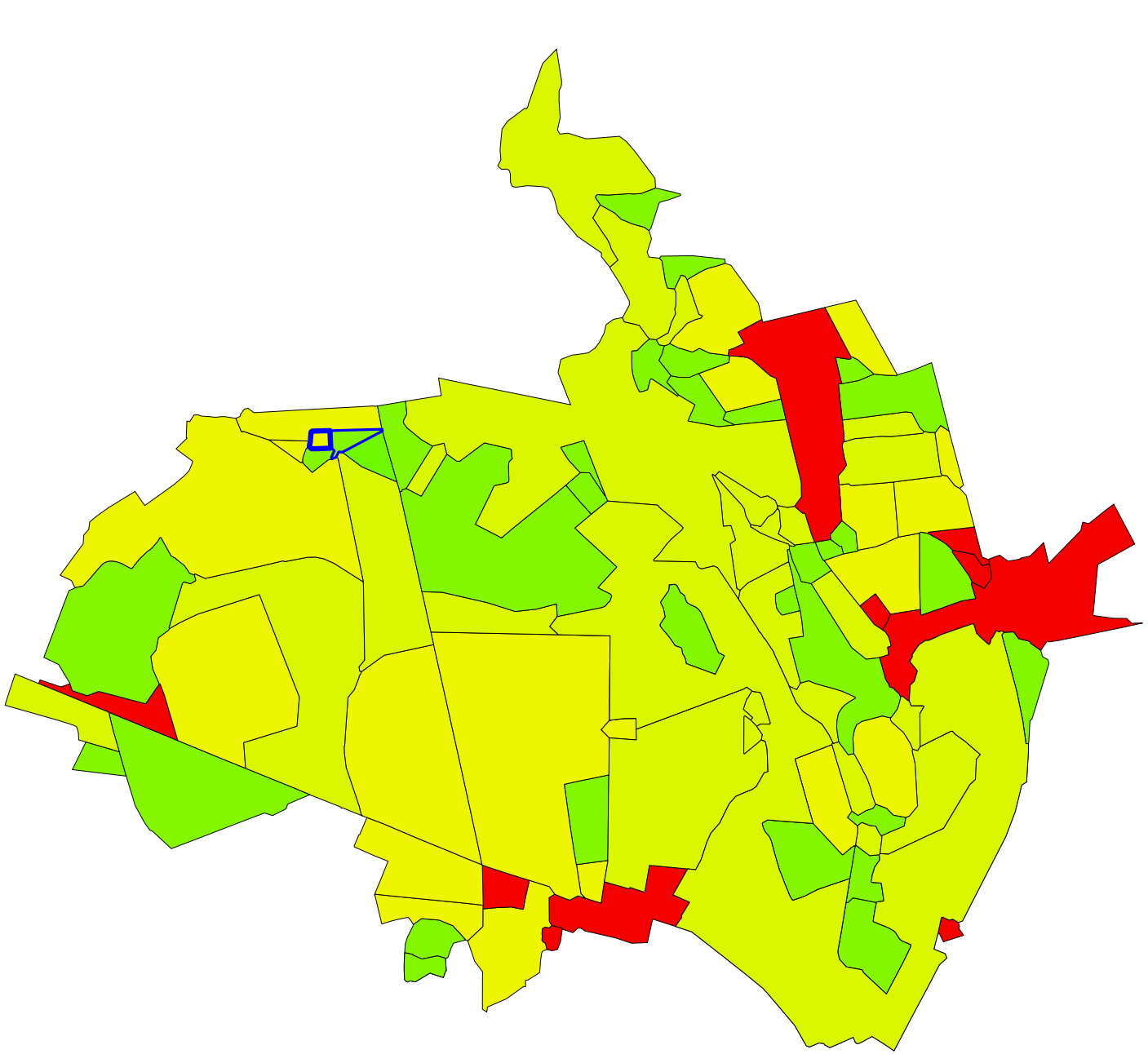


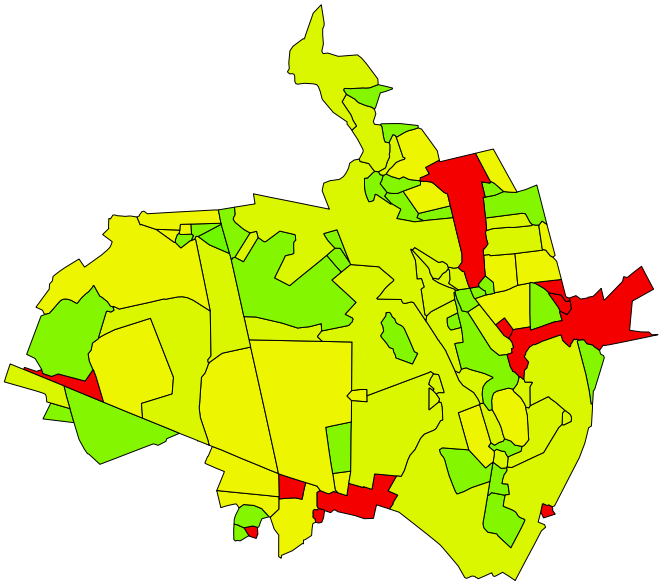


source: 92 patches

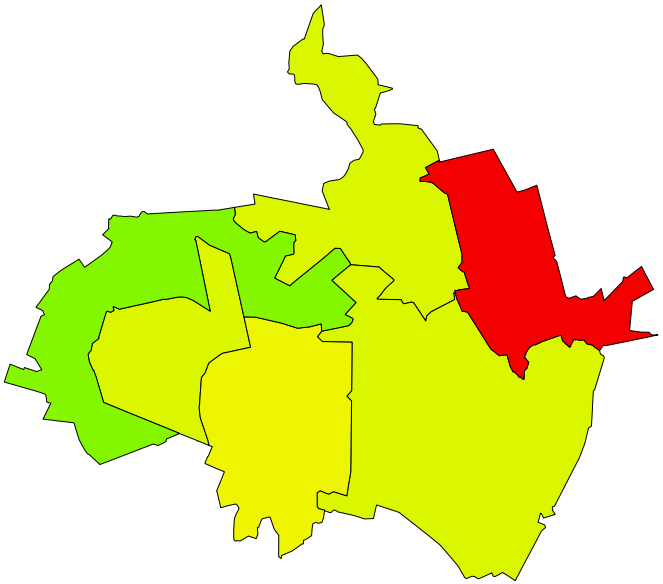


target: 6 patches

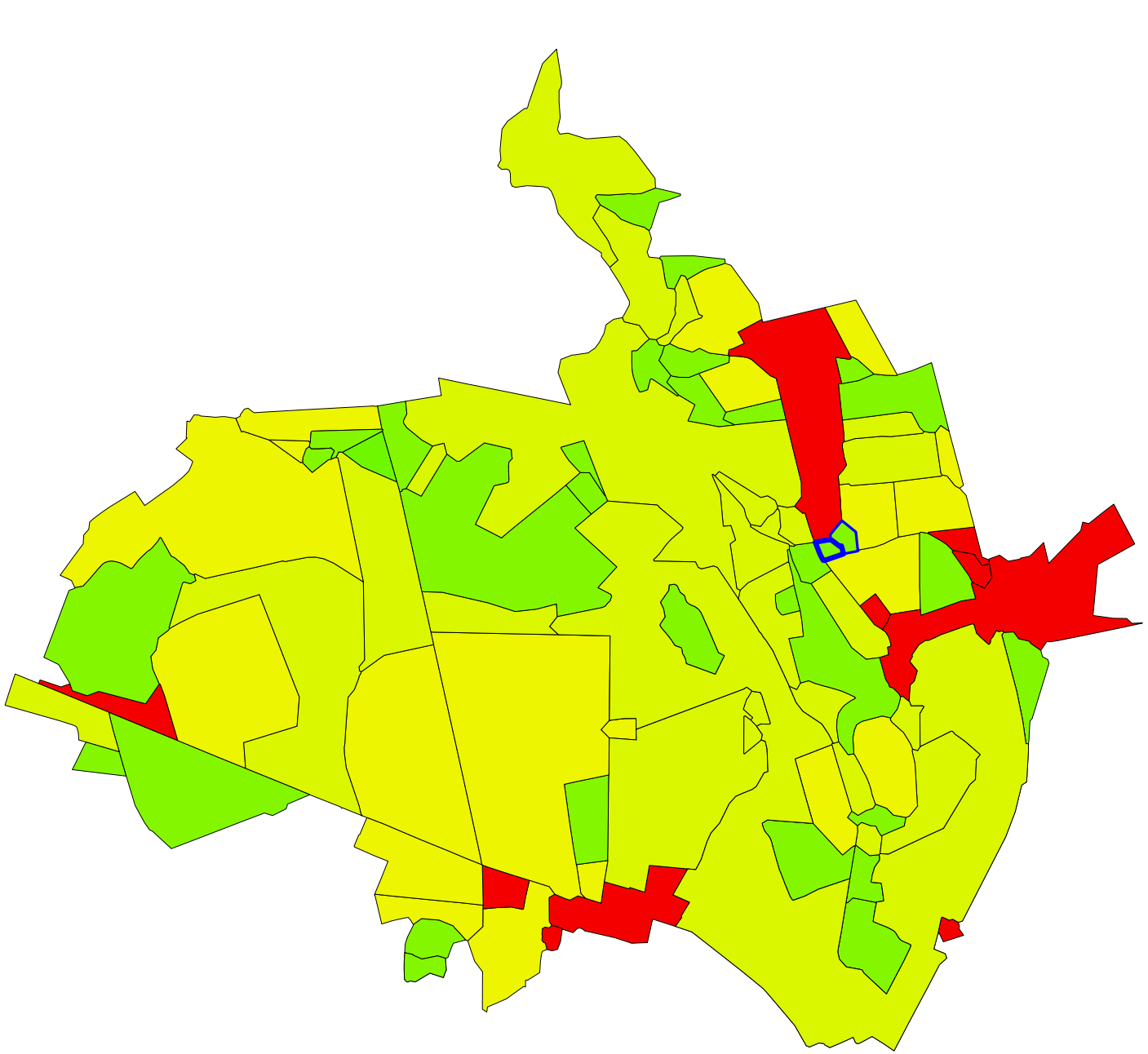


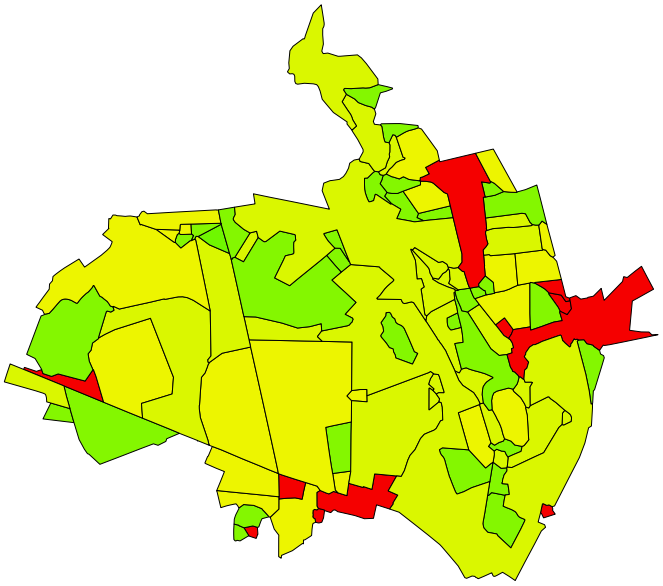


source: 92 patches

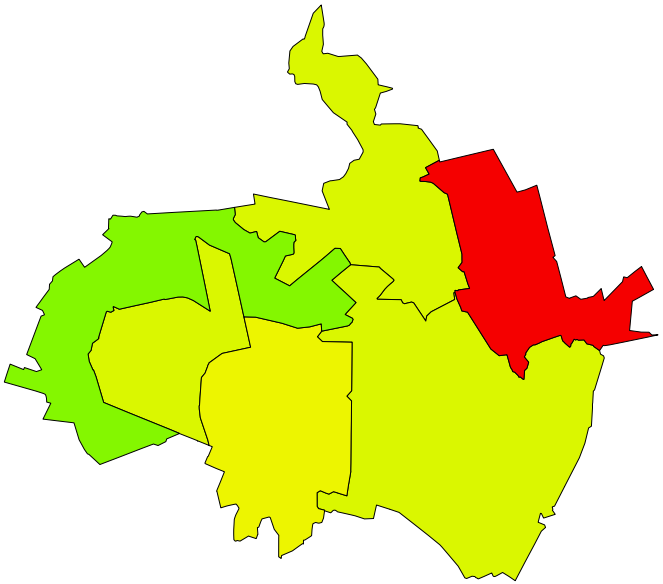


target: 6 patches

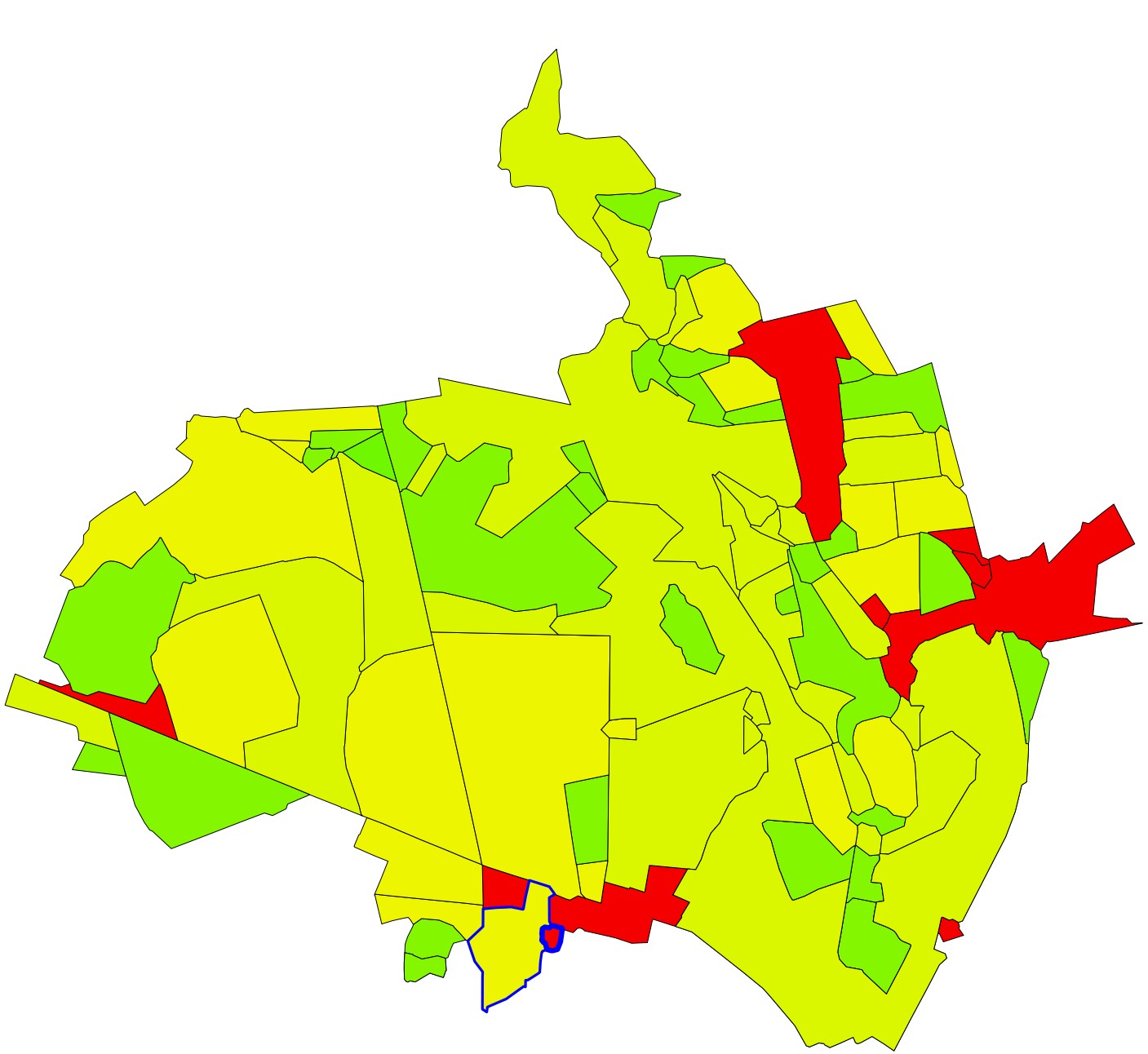


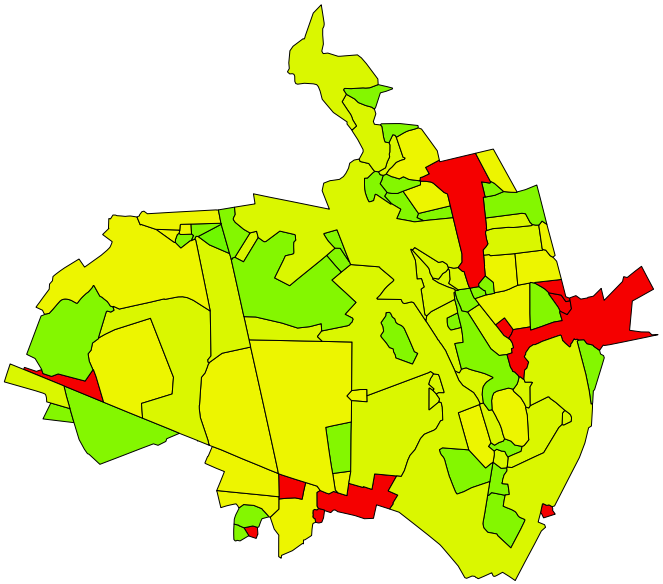


source: 92 patches

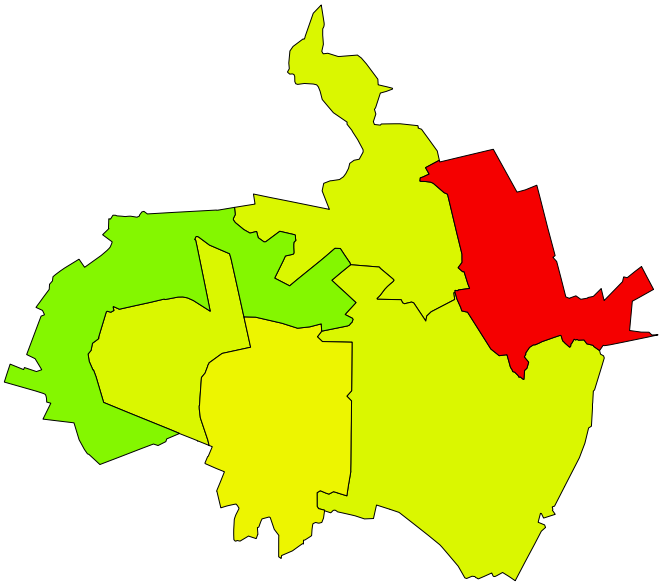


target: 6 patches

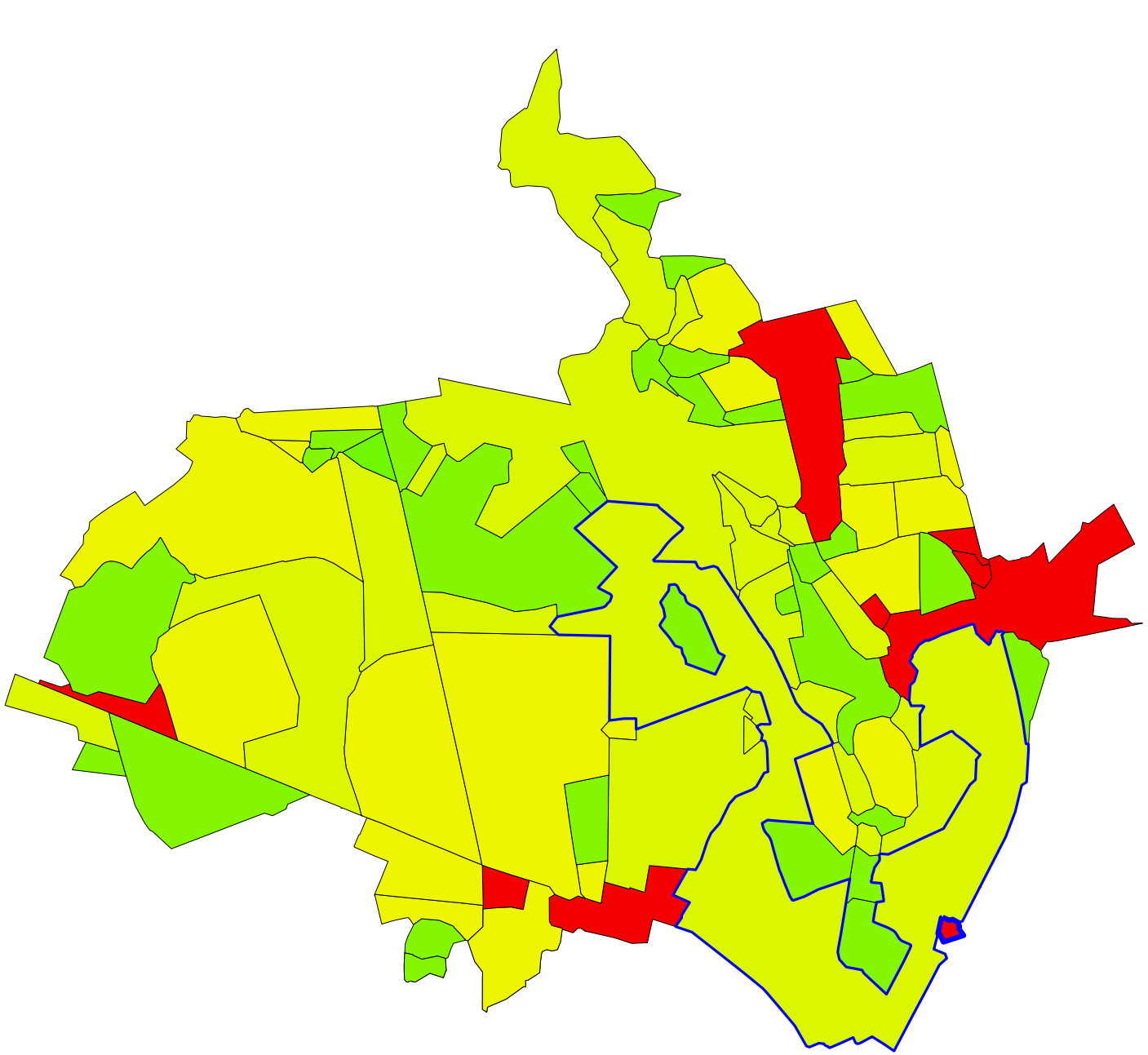


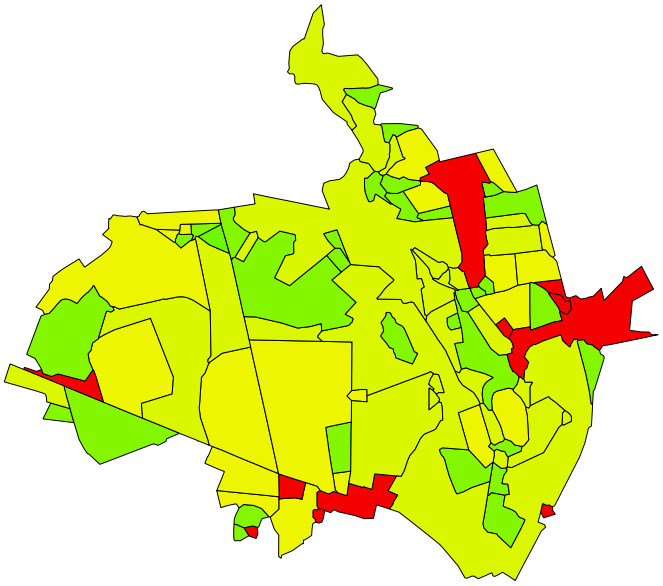


source: 92 patches

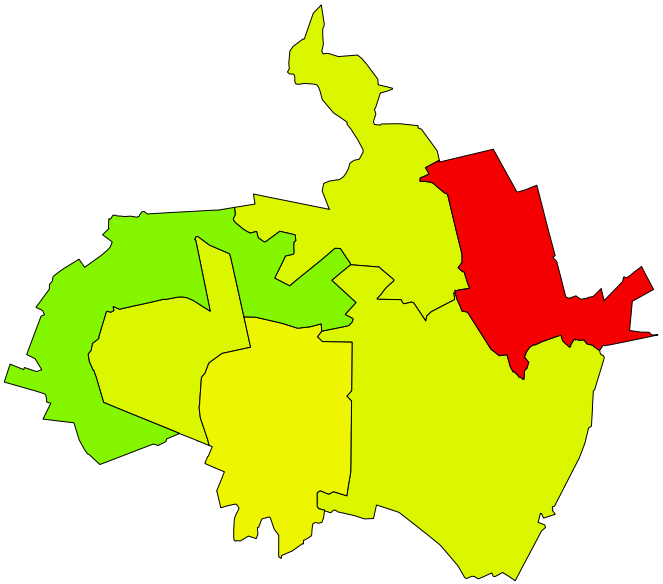


target: 6 patches





source: 92 patches



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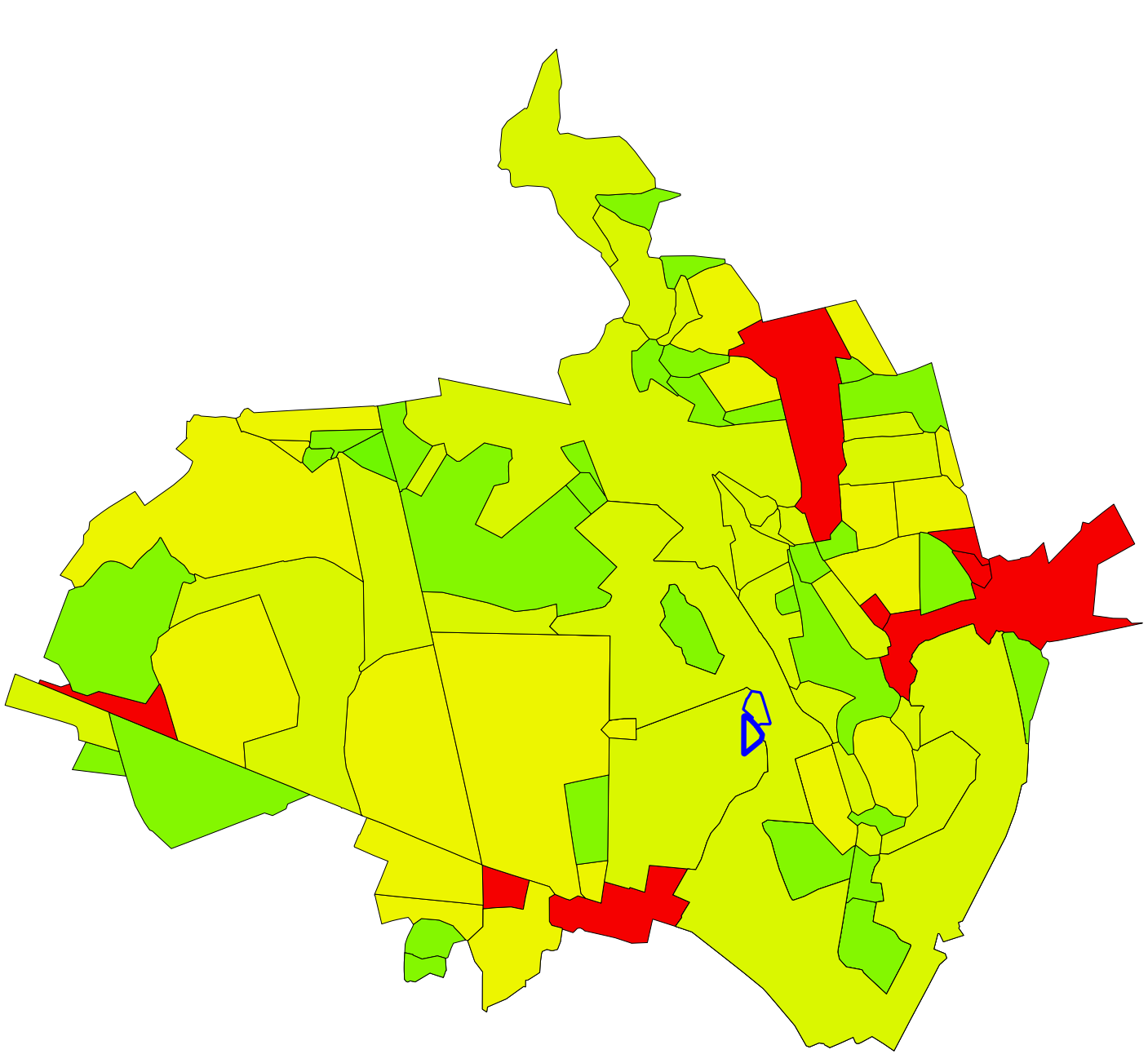
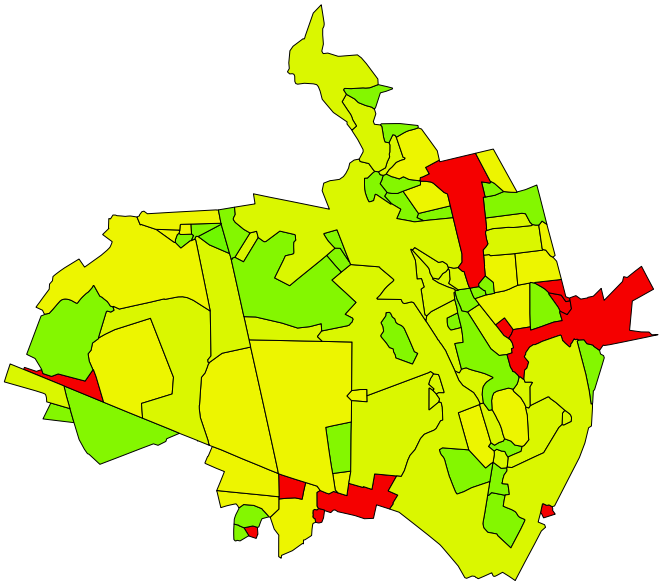
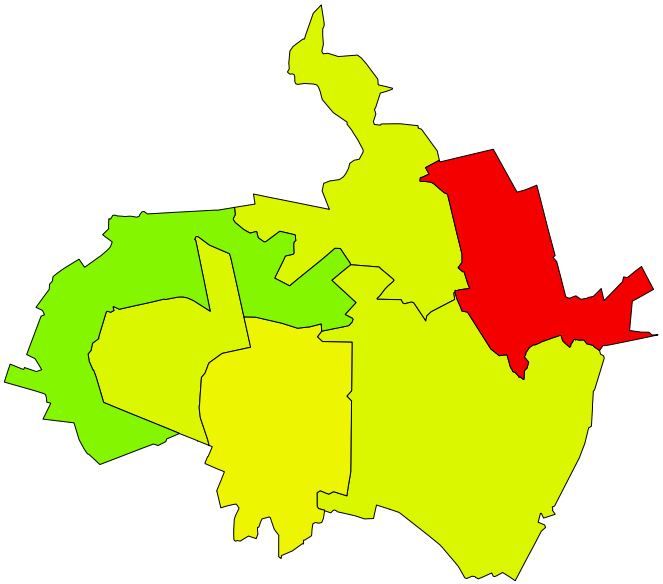
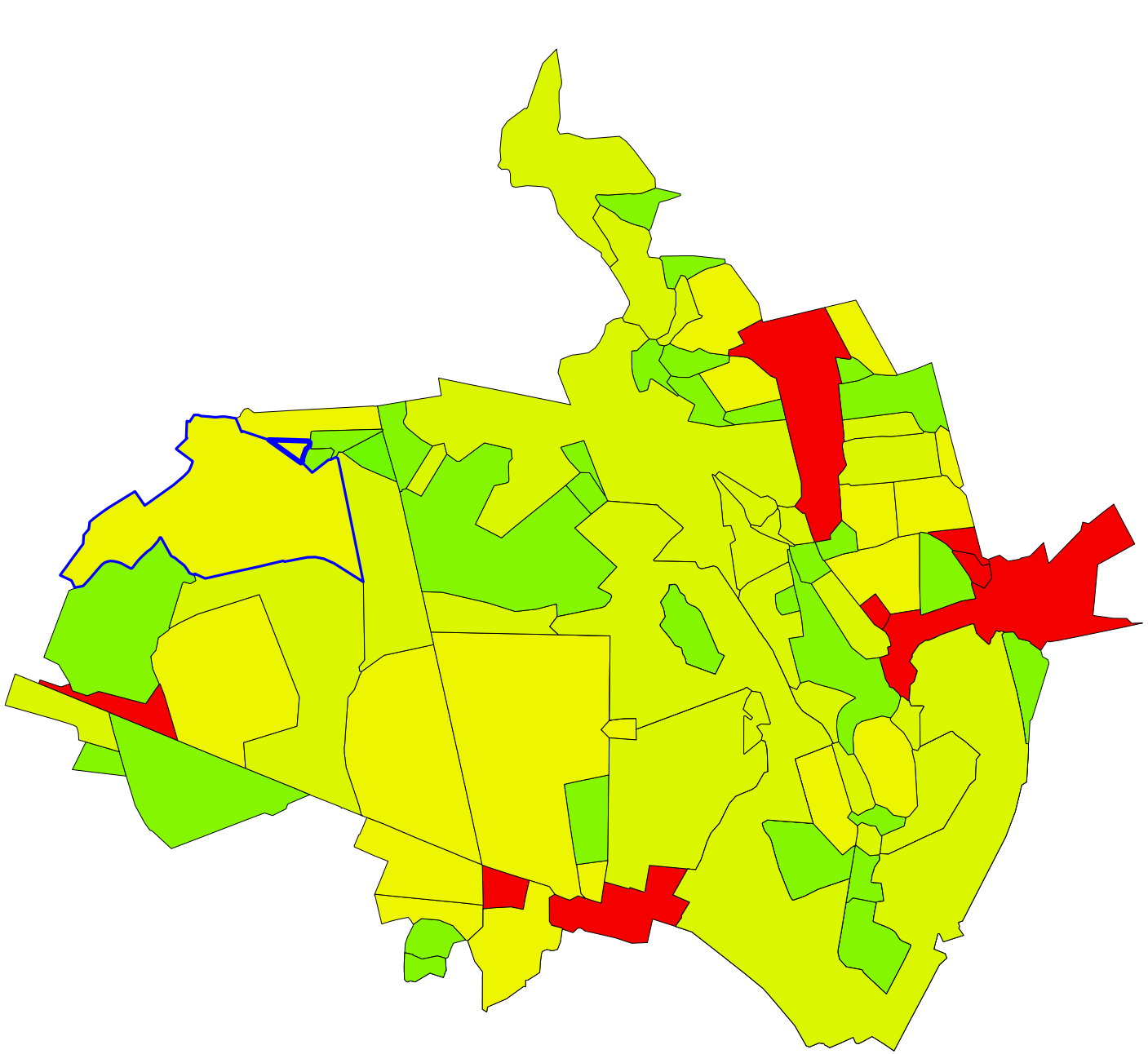


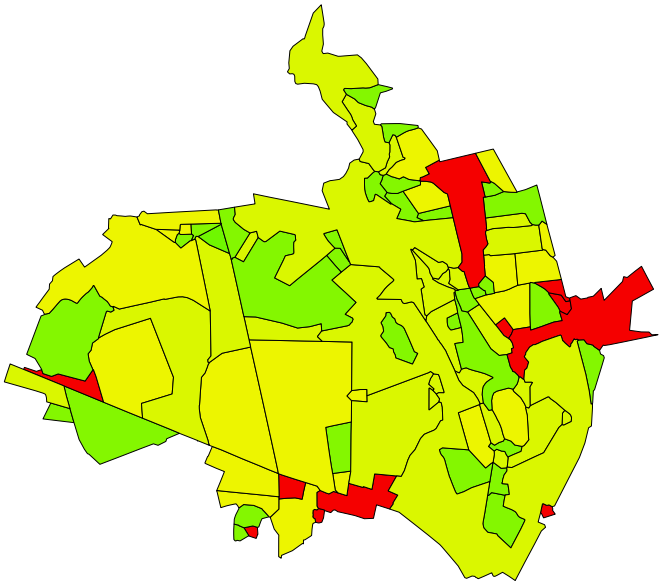


source: 92 patches

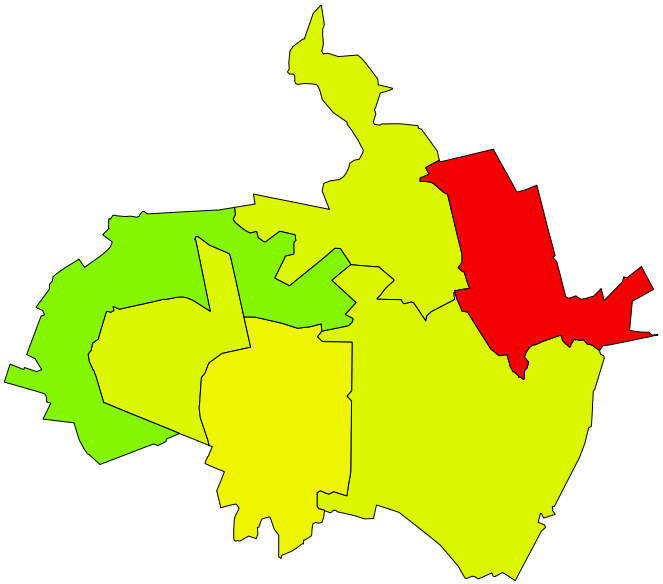


target: 6 patches

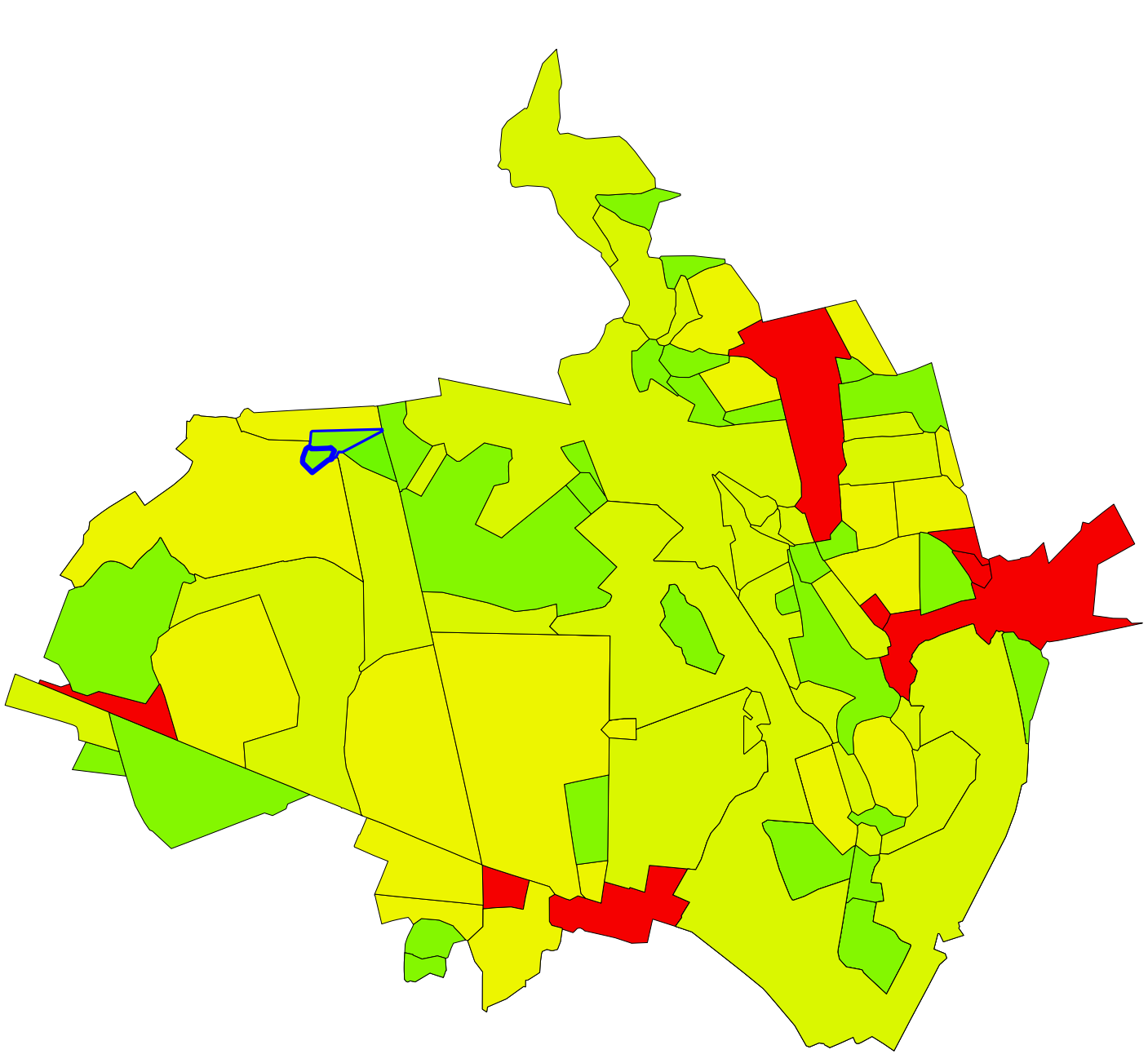


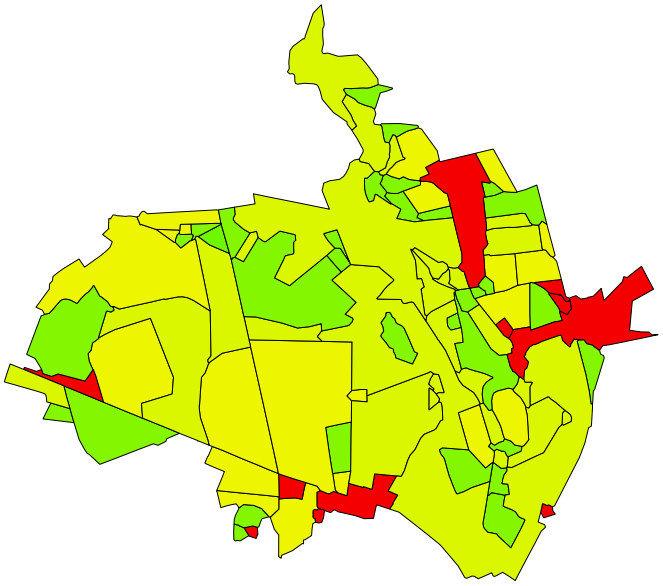


source: 92 patches

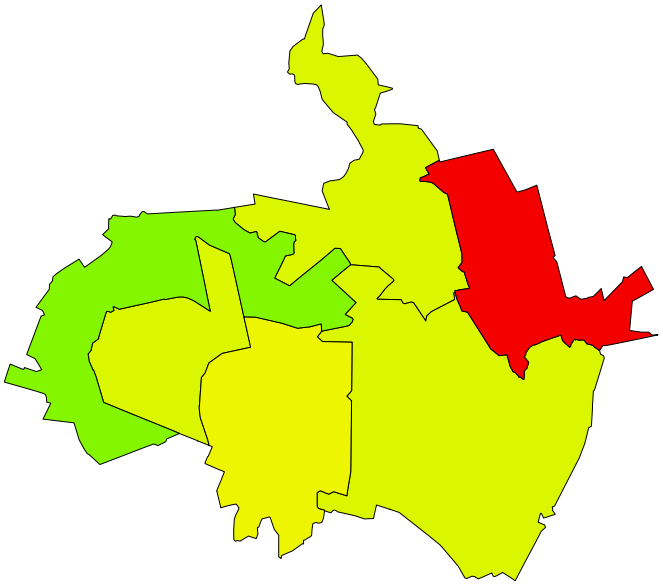


target: 6 patches





source: 92 patches



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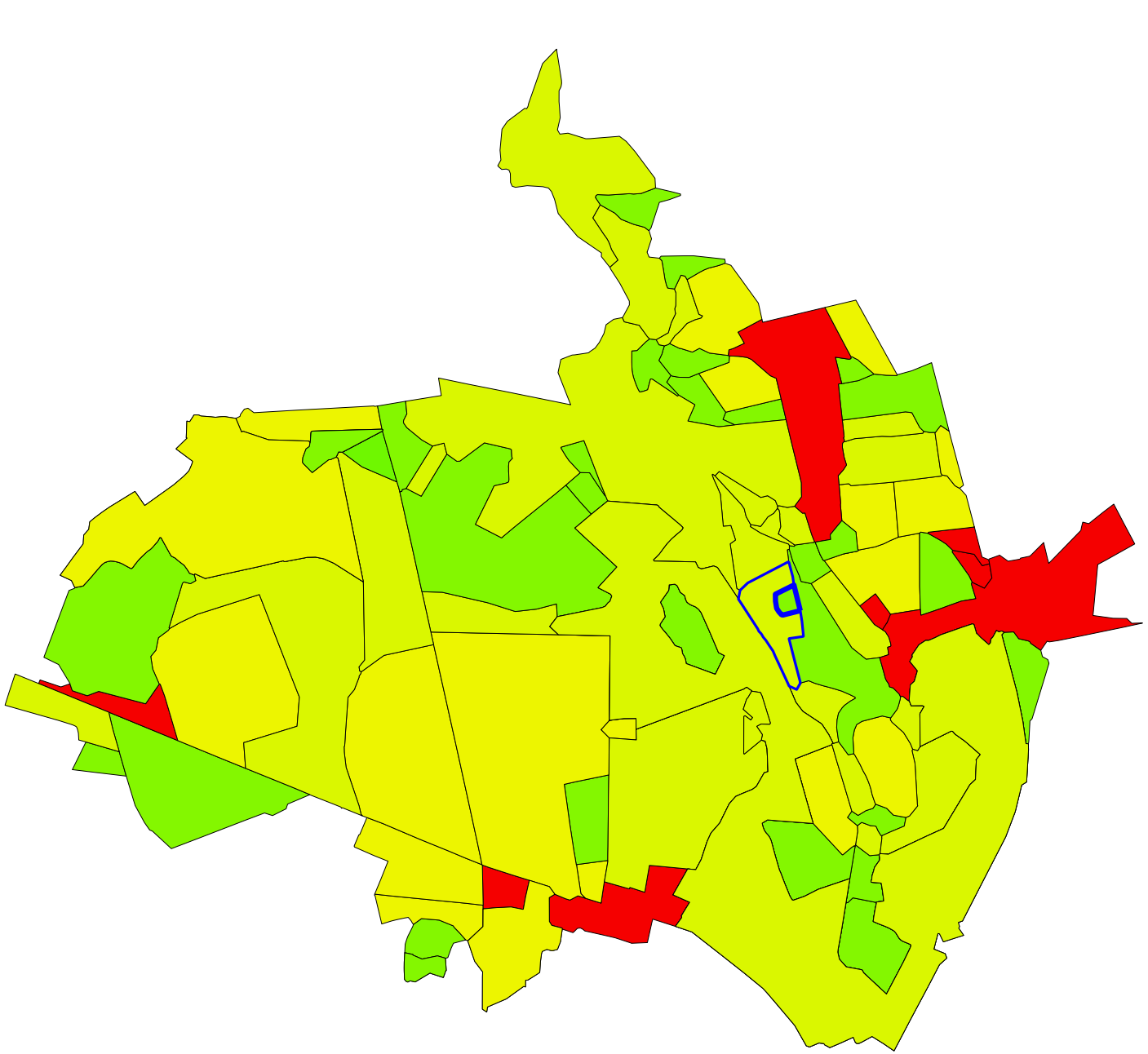
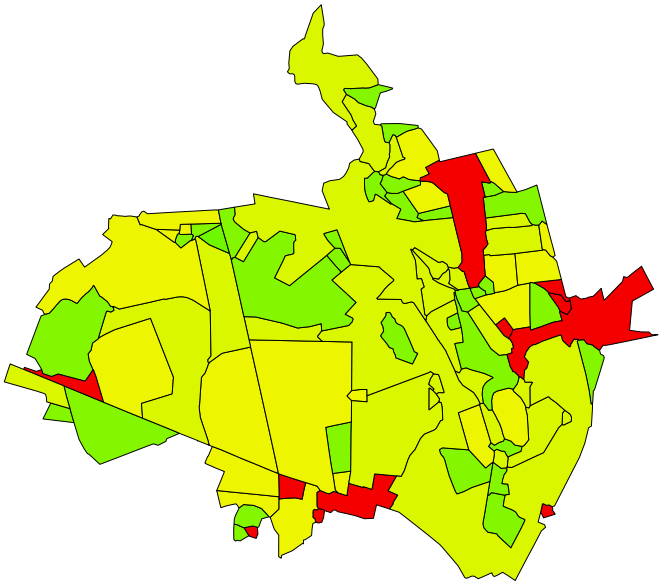
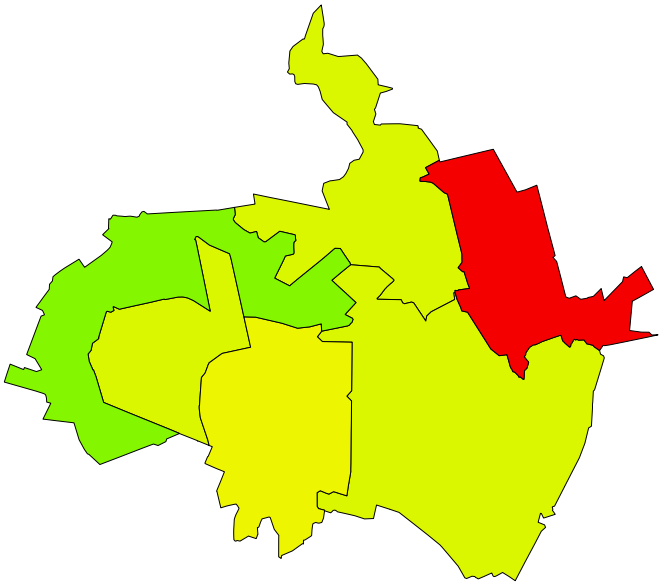




source: 92 patches



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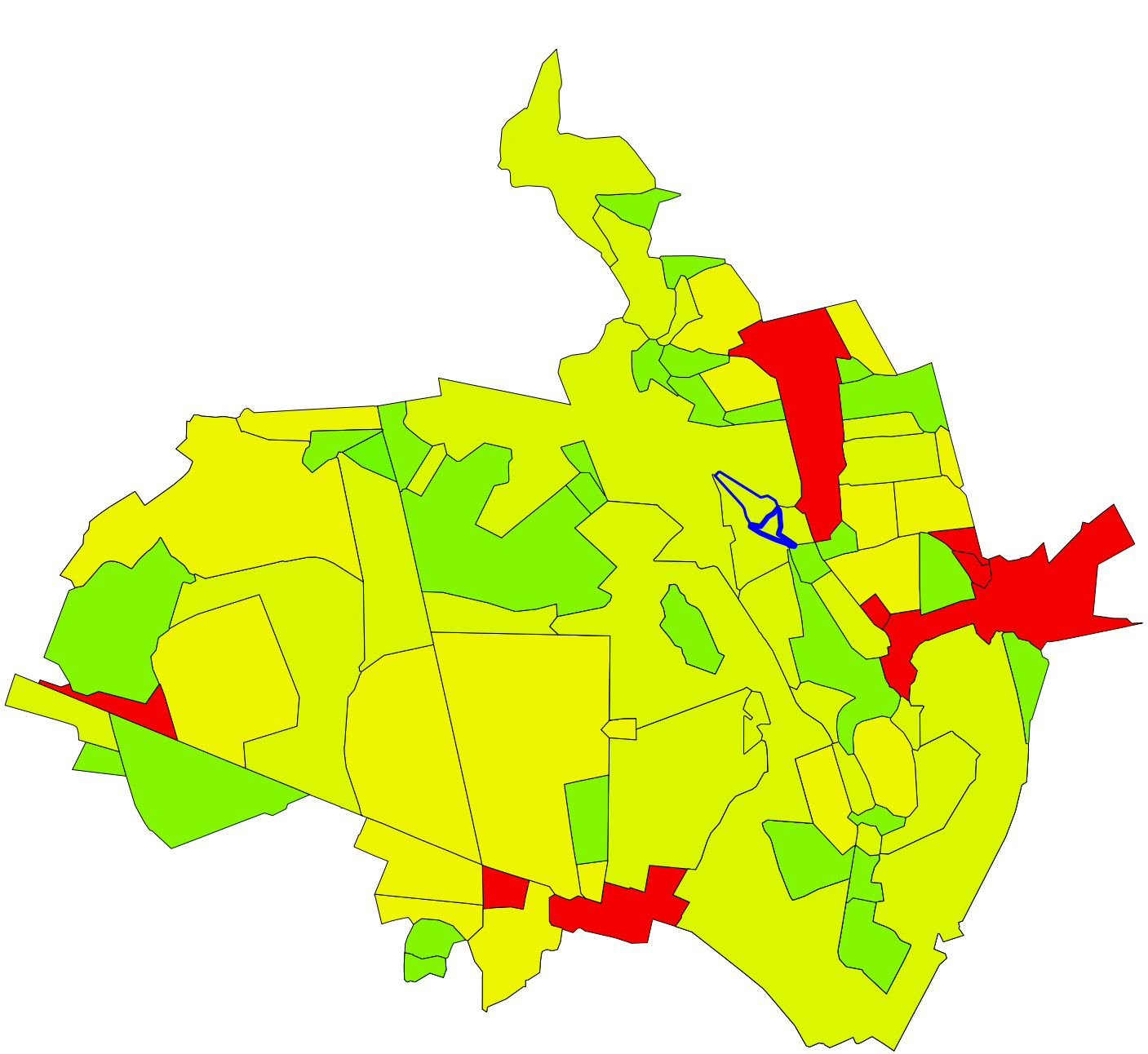
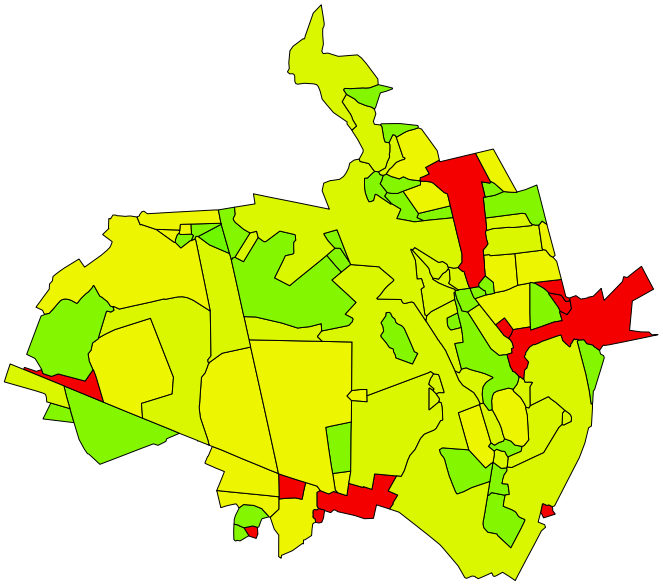
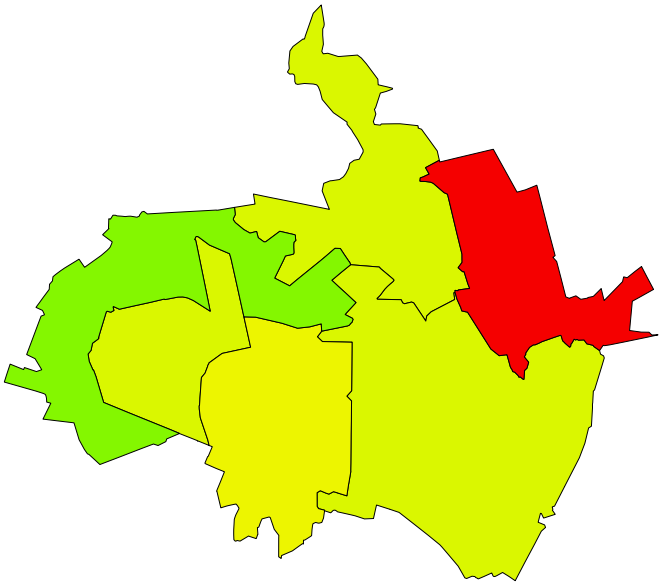
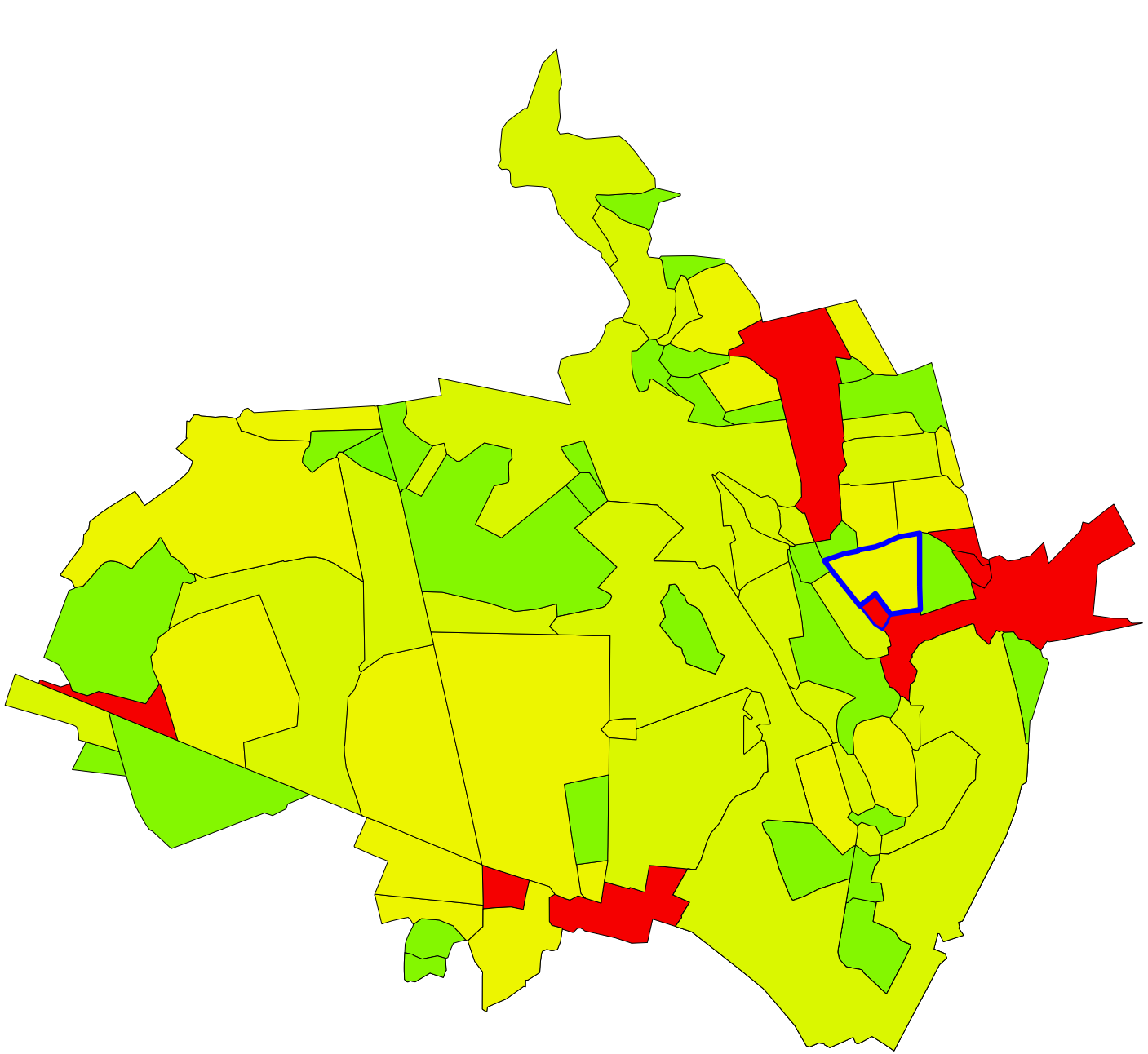


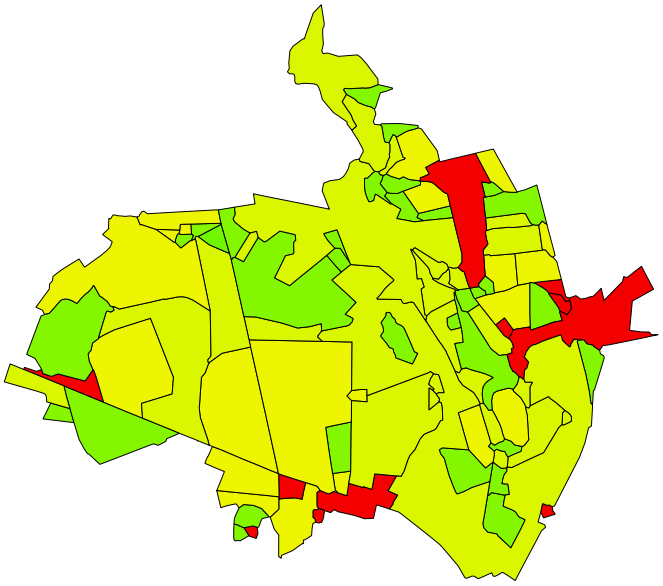


source: 92 patches

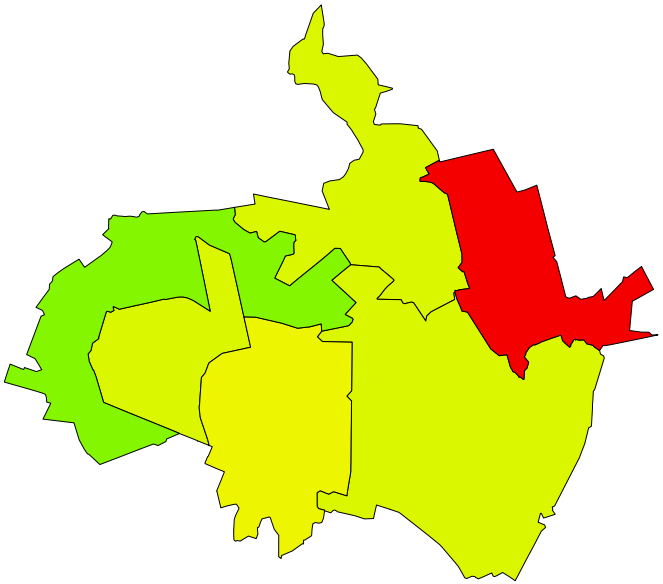


target: 6 patches





source: 92 patches



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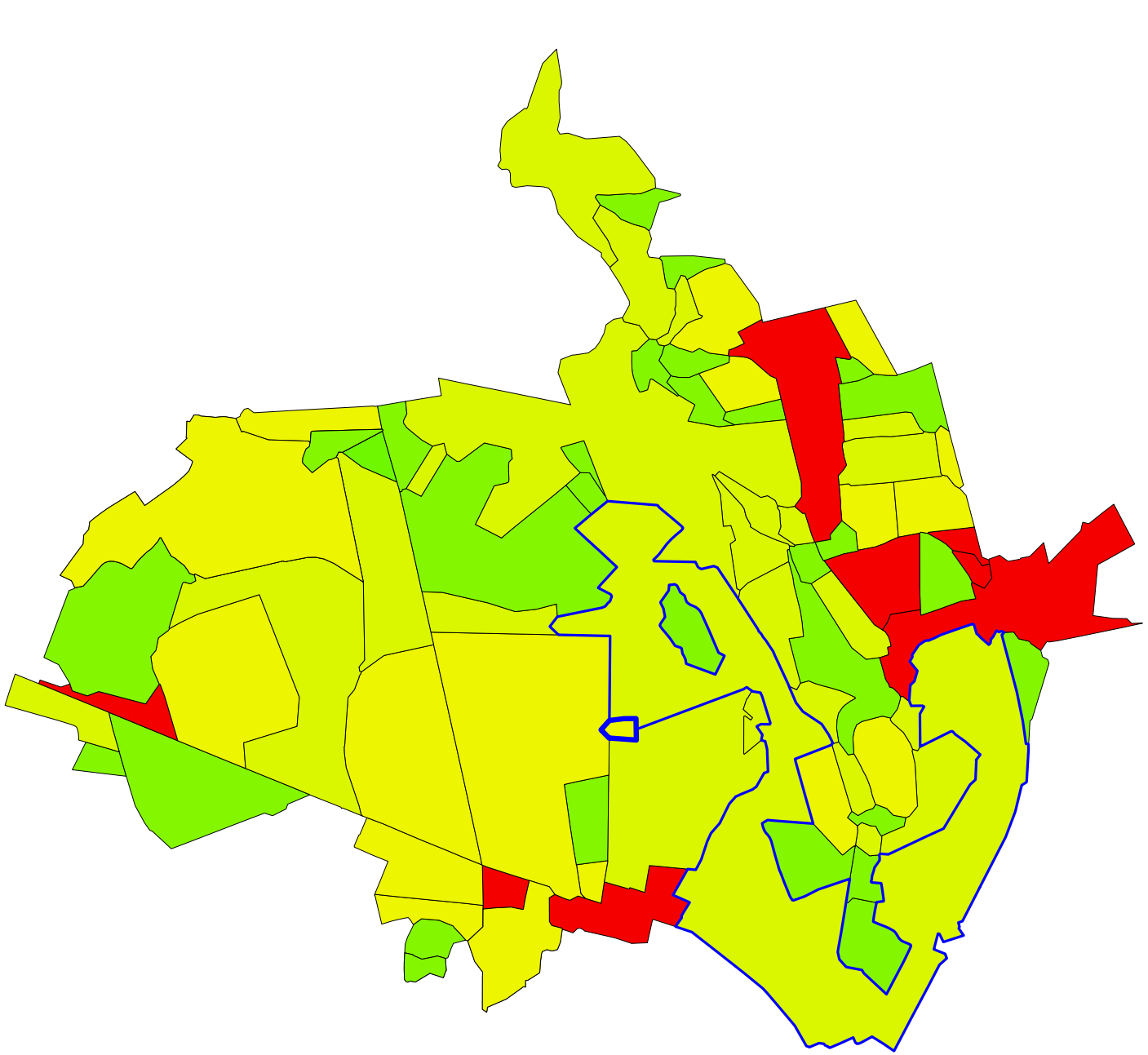

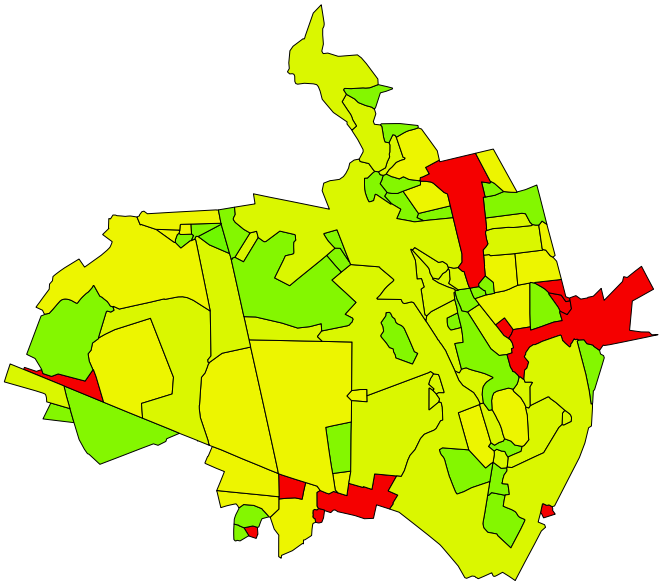

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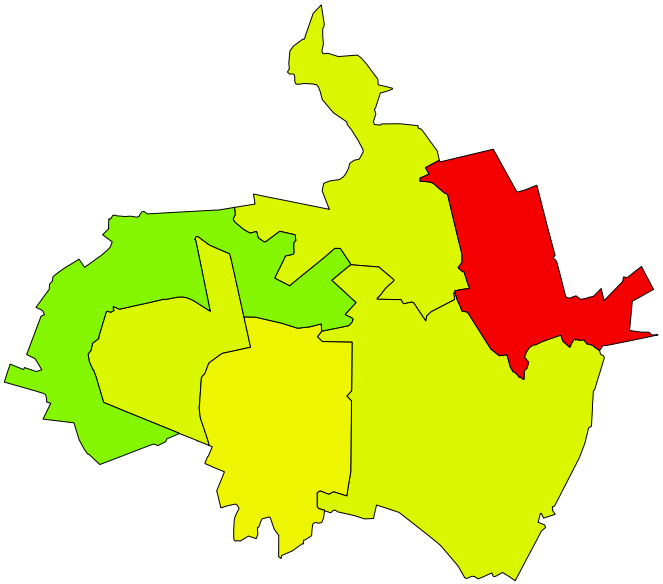

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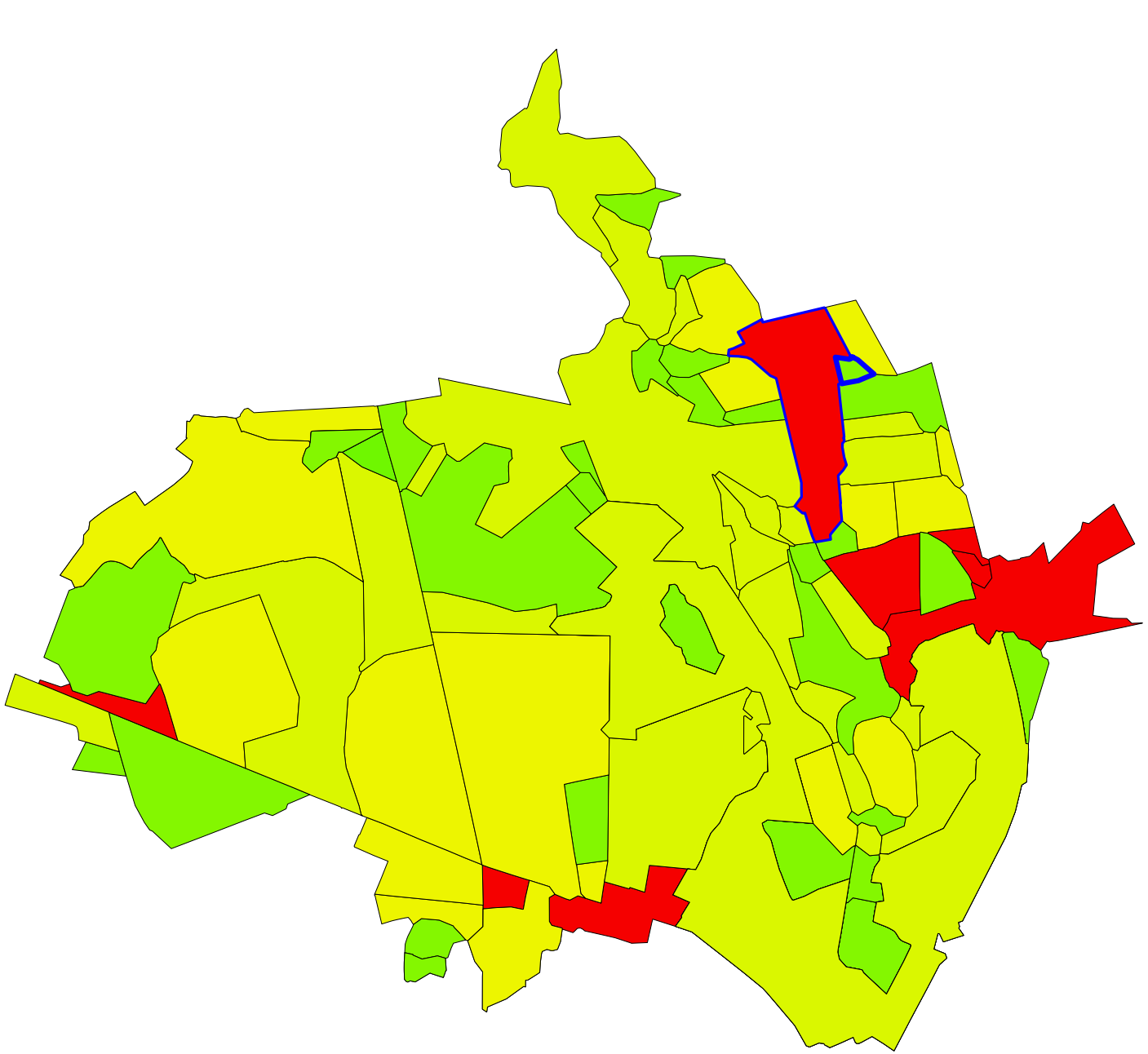

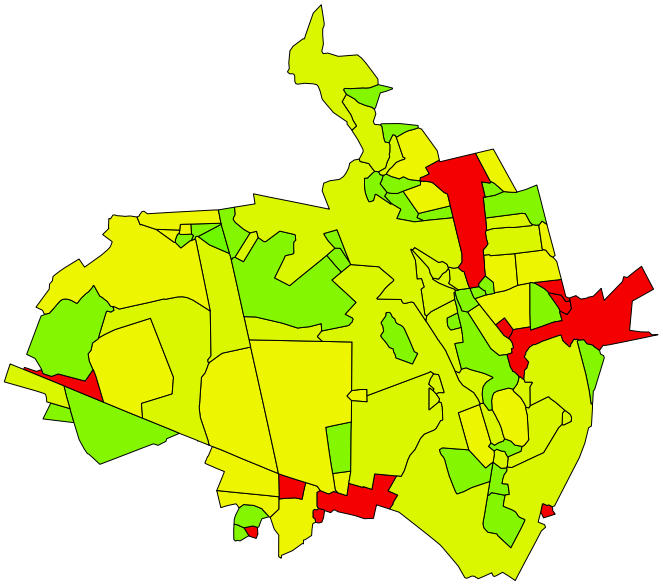

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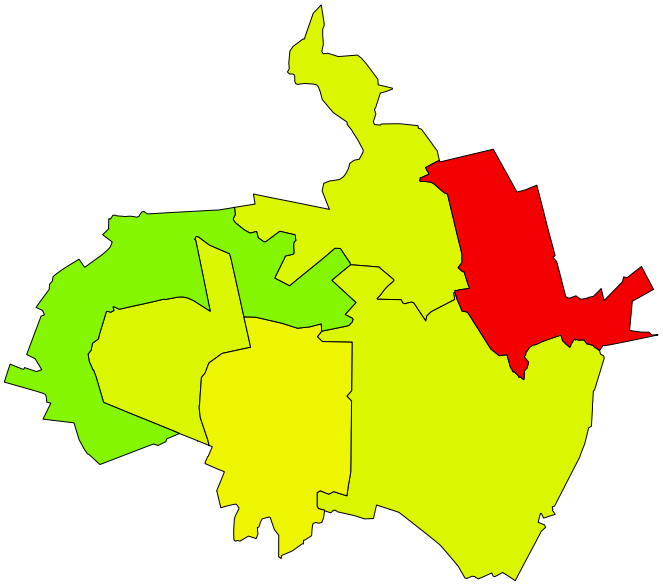

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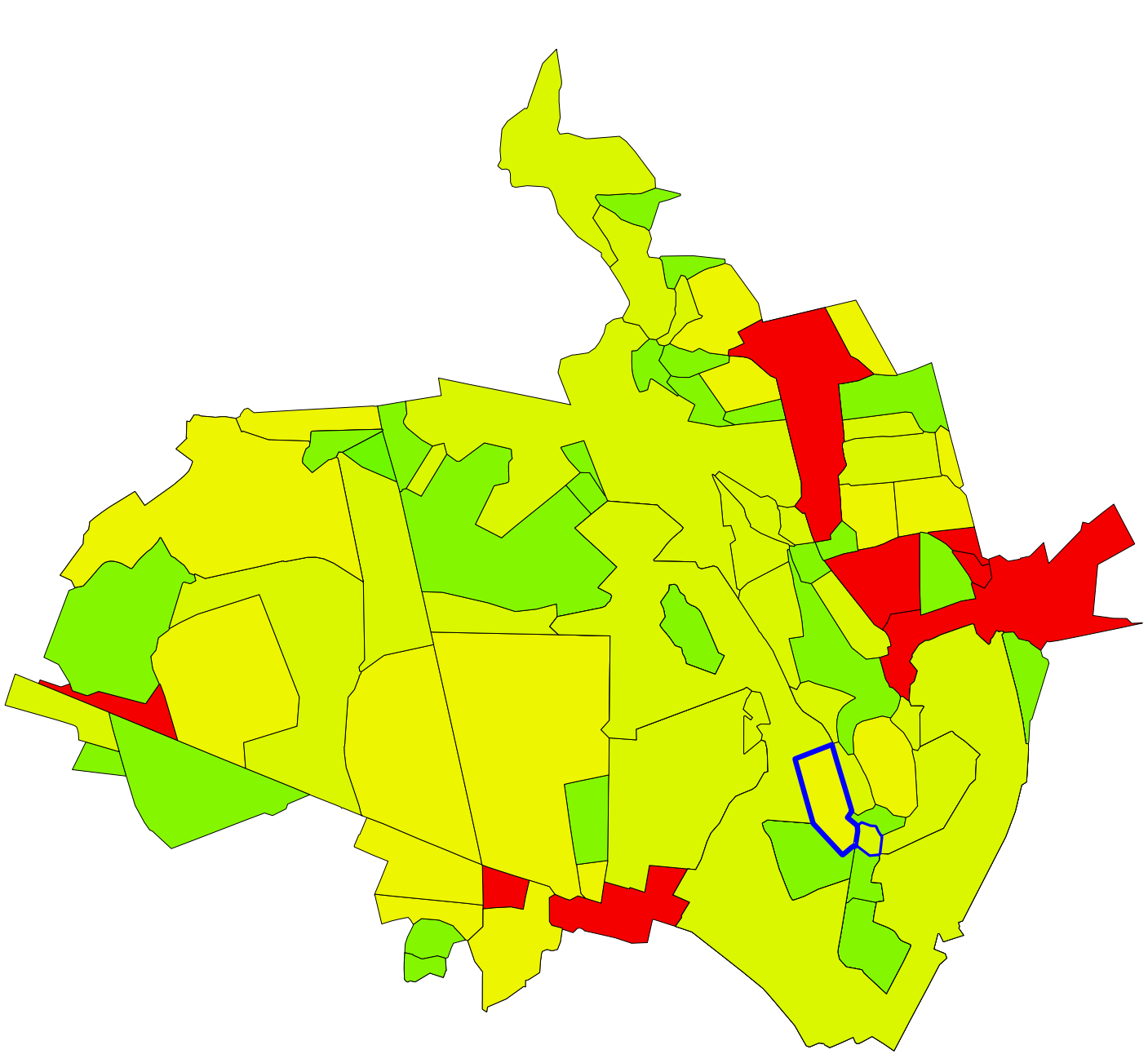

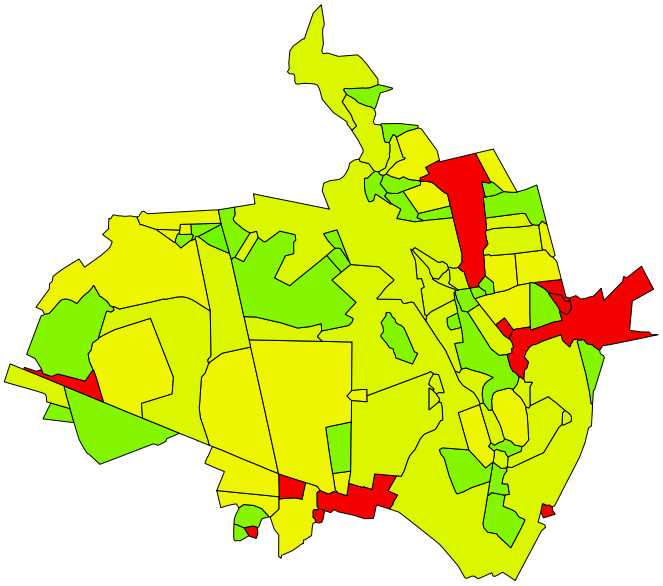

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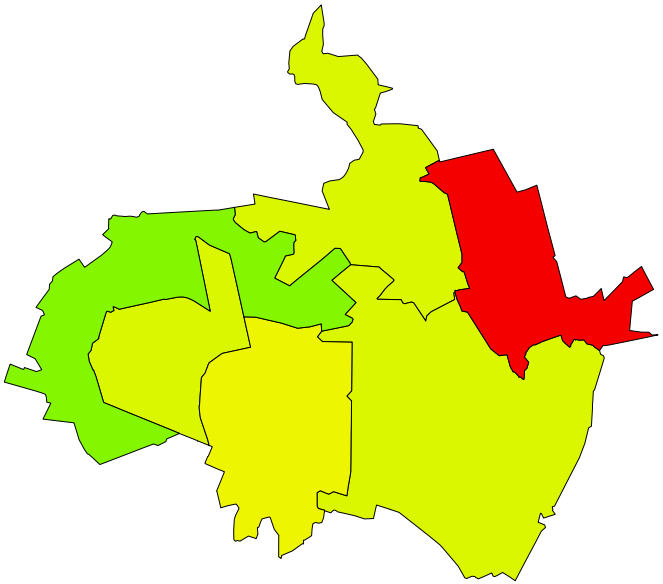

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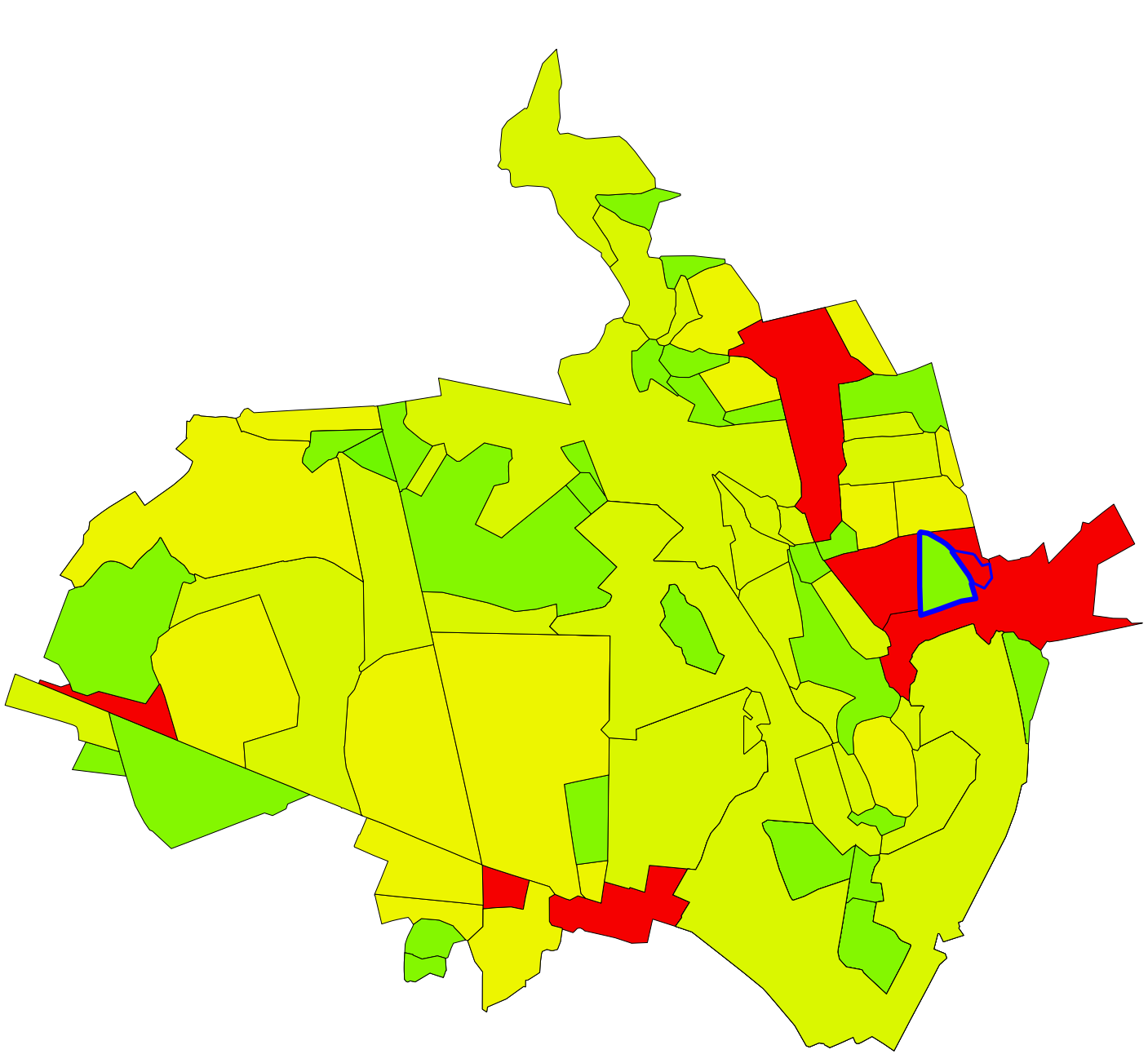

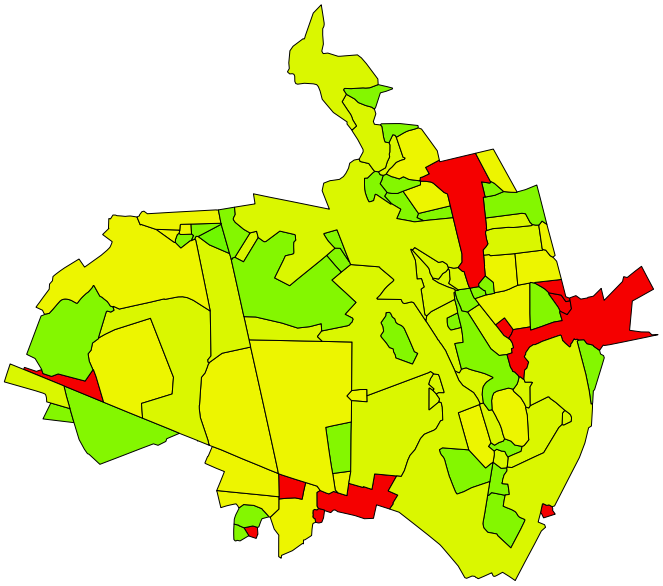

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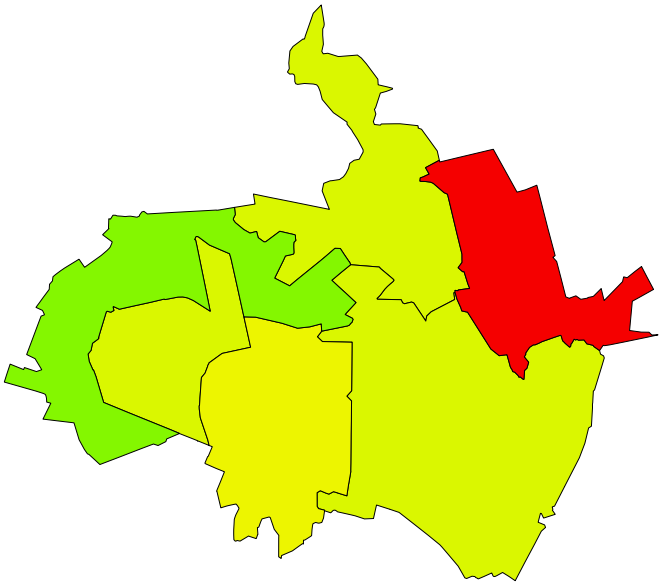

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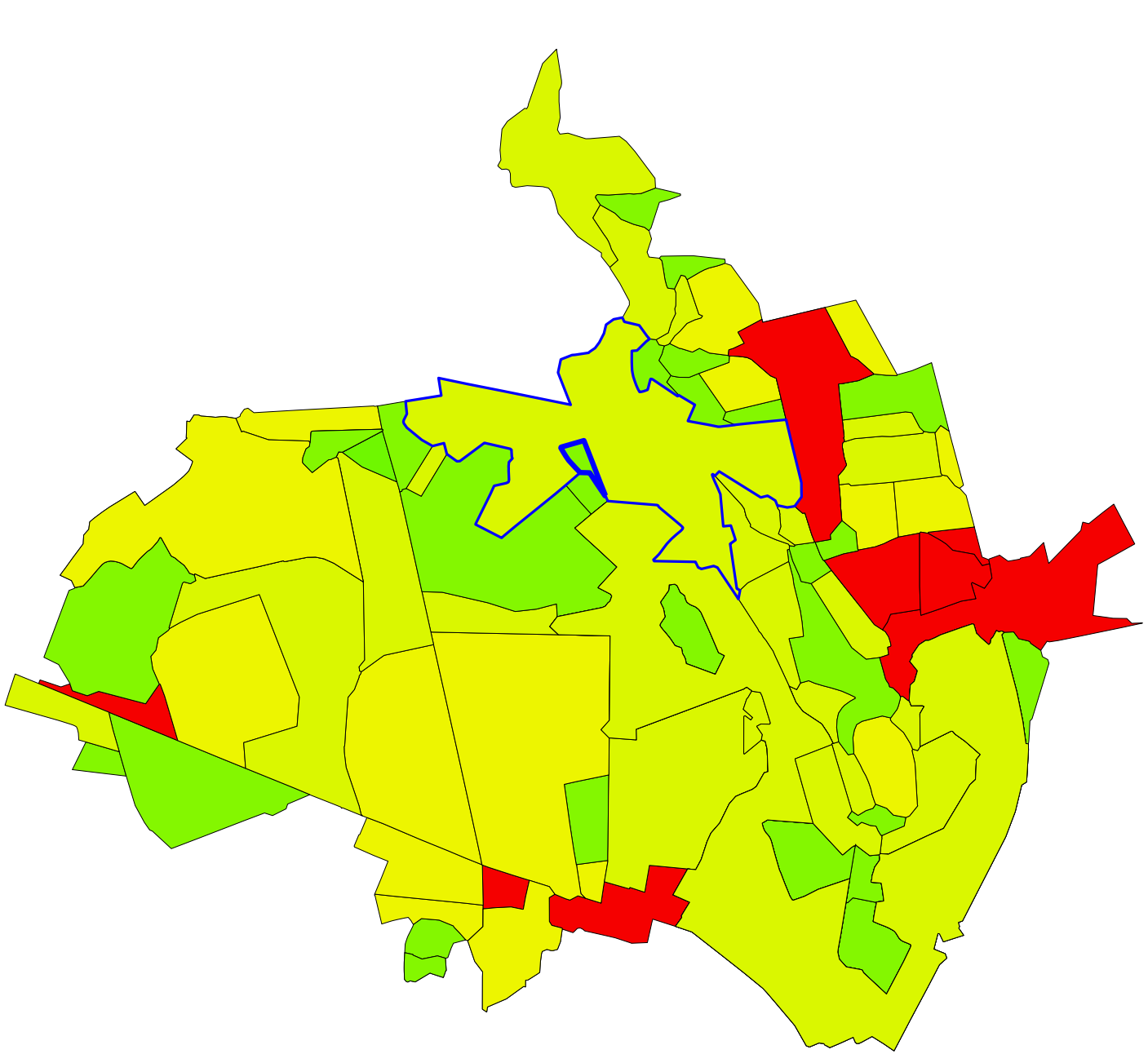

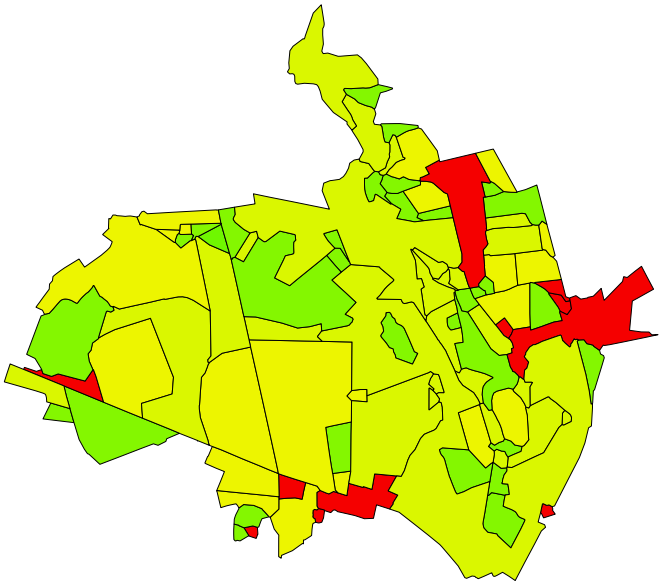

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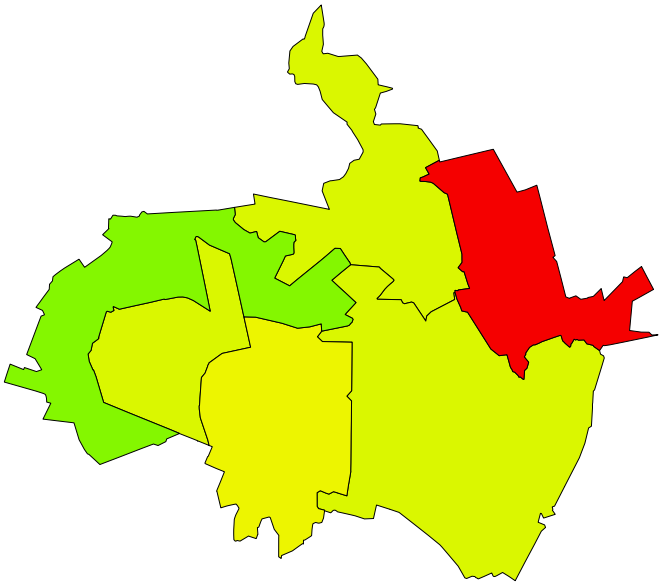

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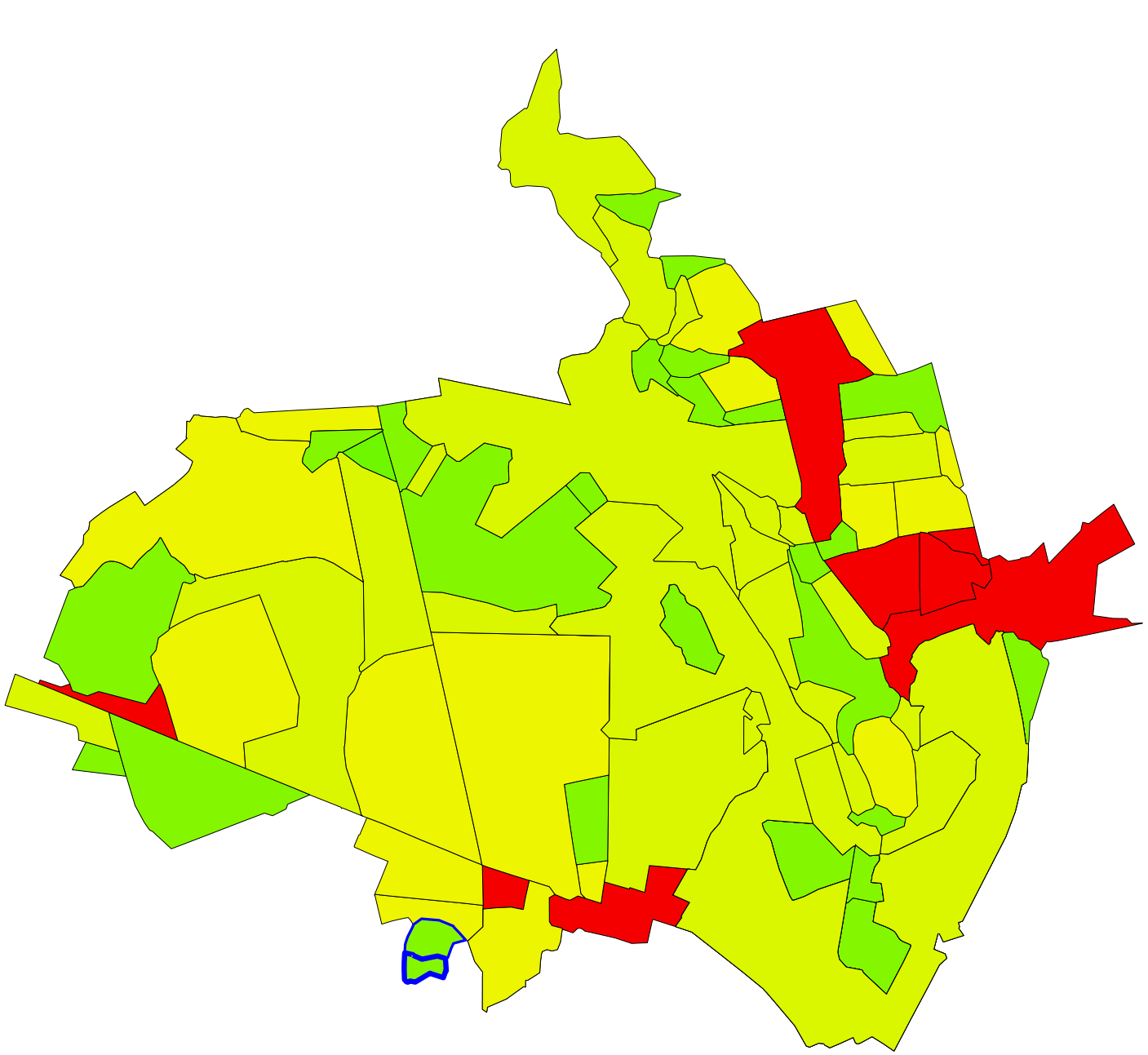

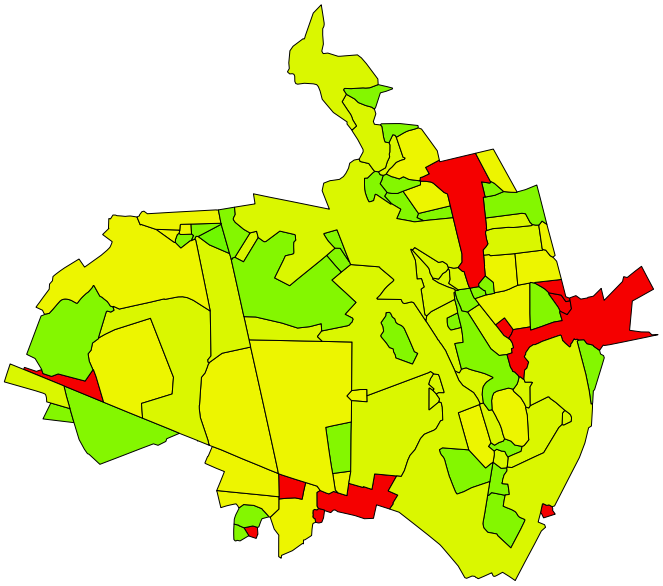

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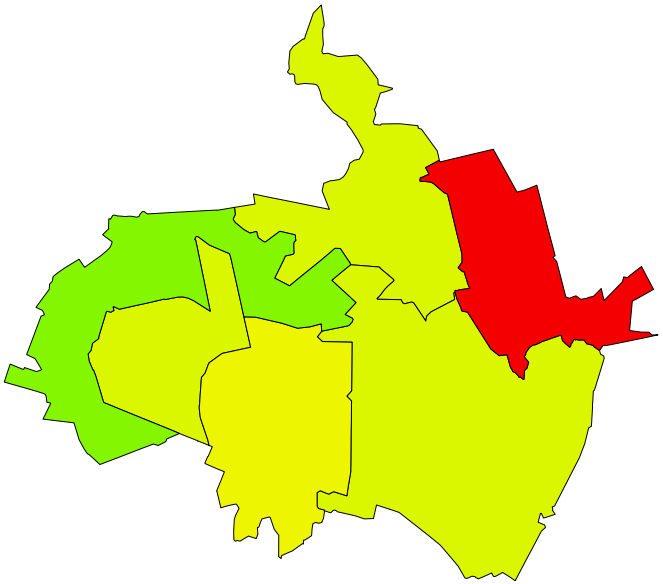

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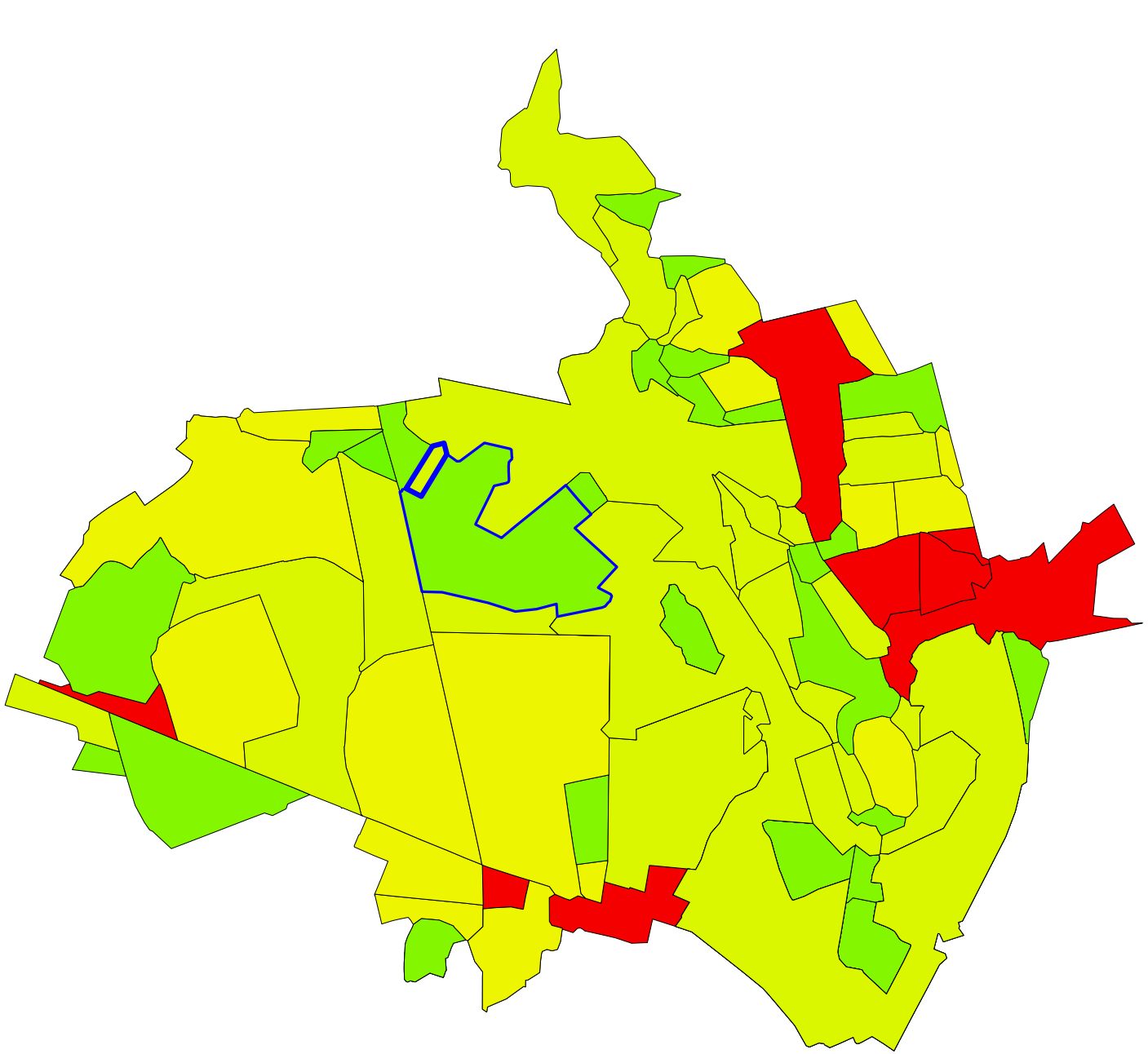

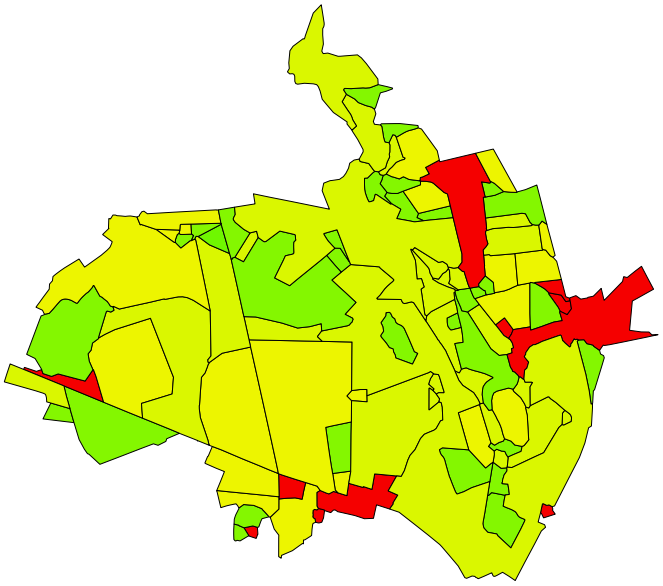

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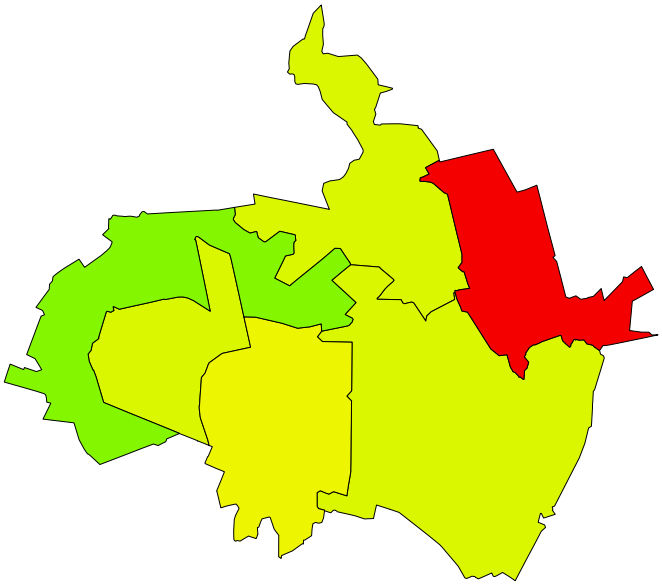

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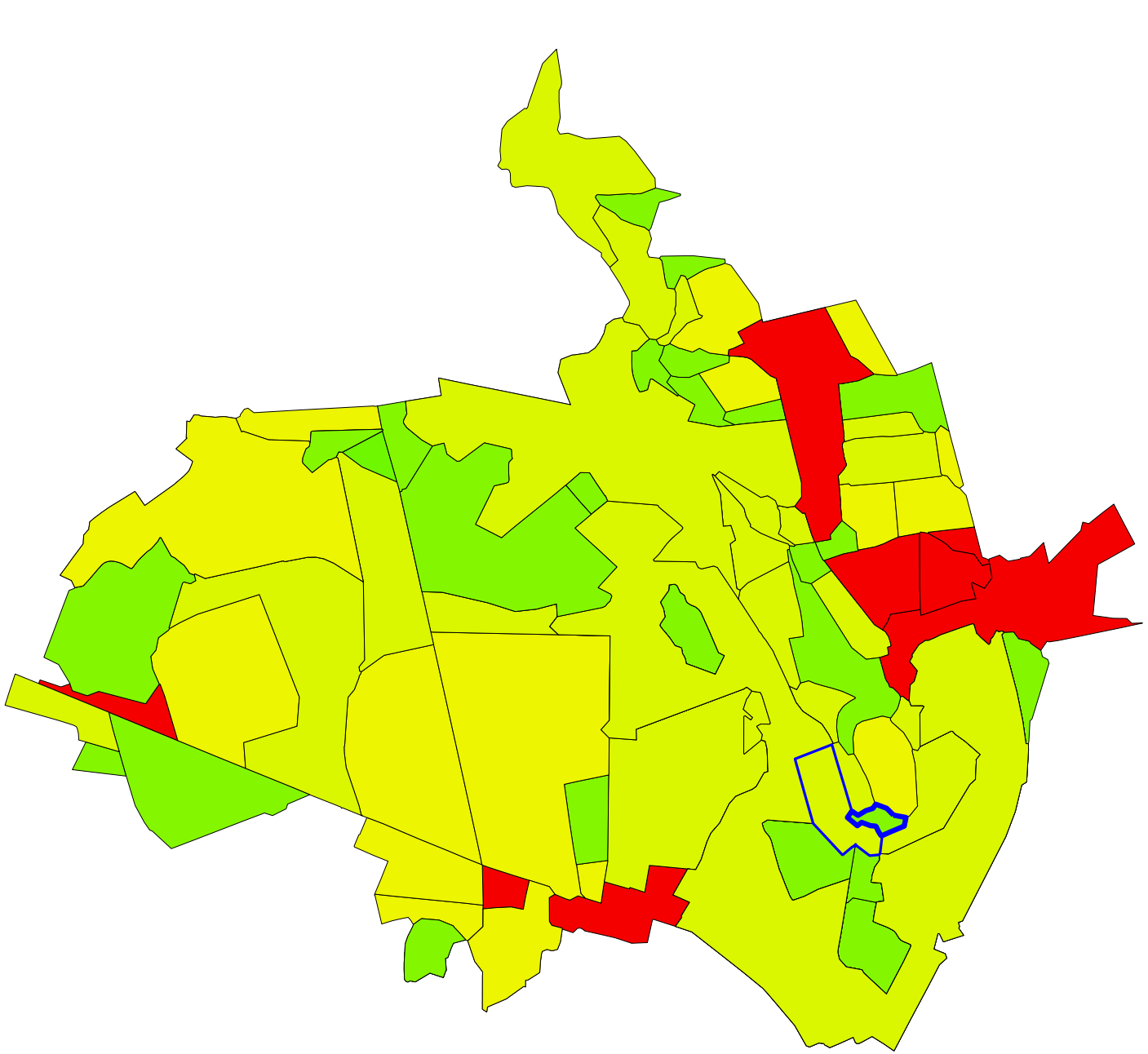

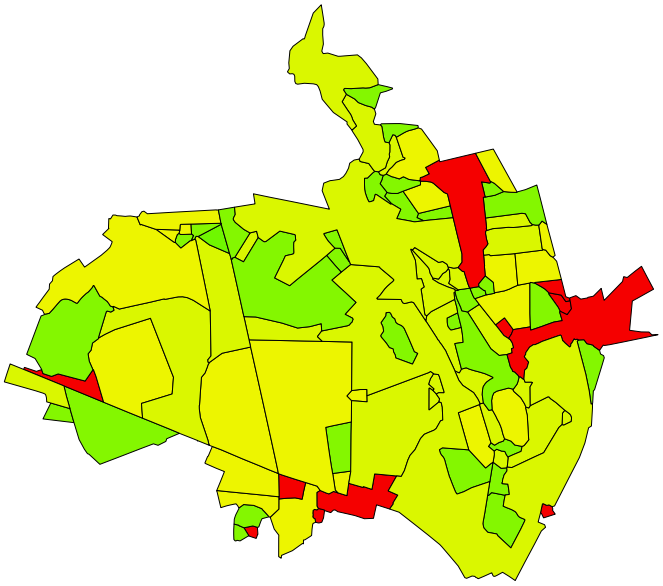

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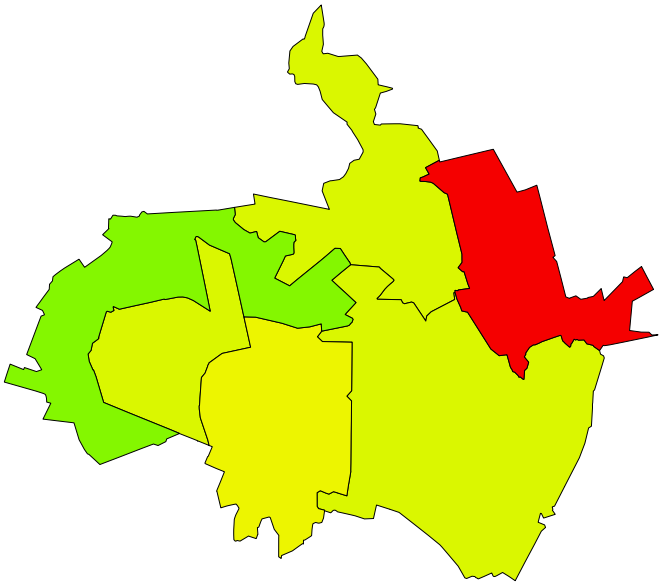

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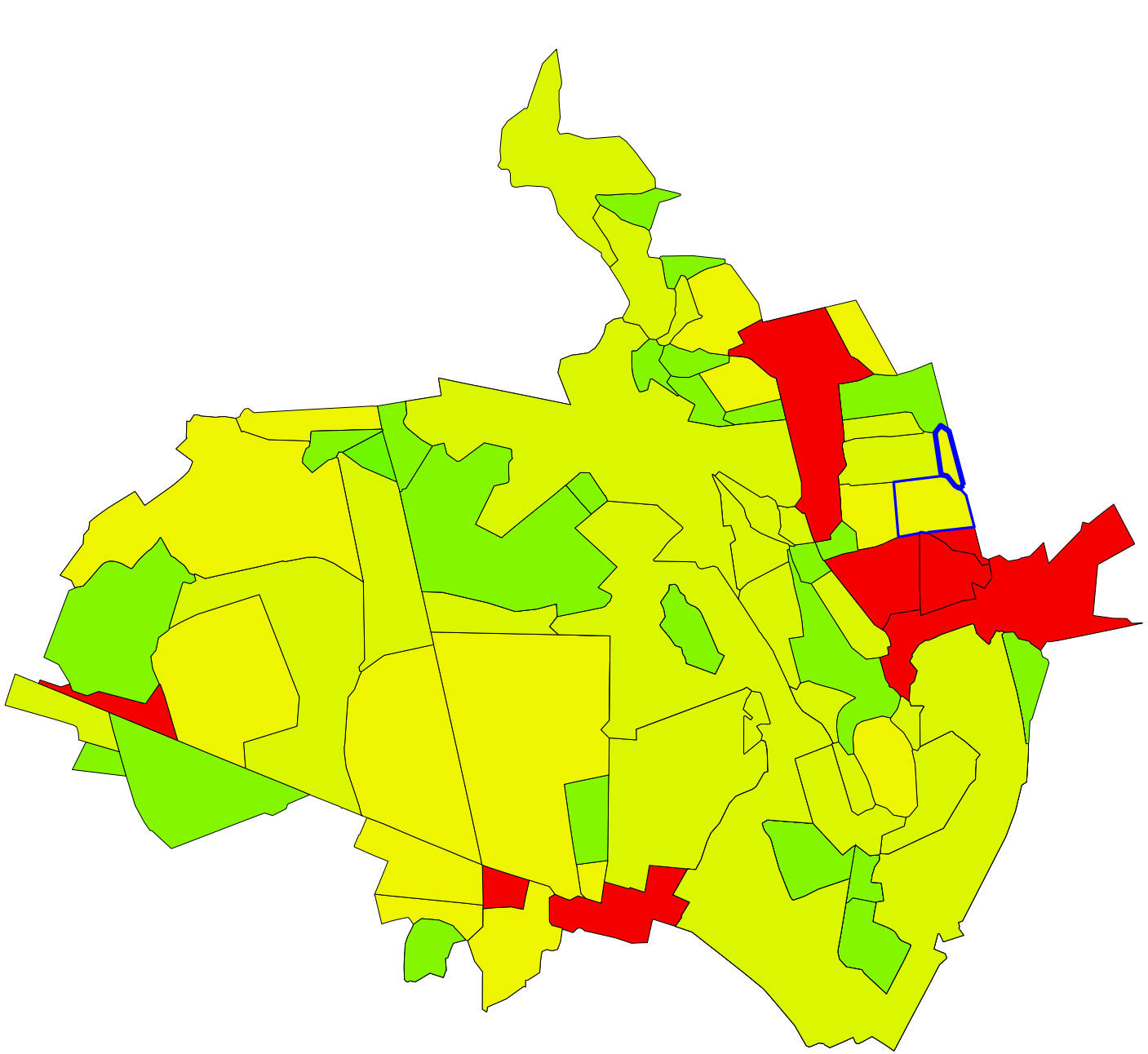

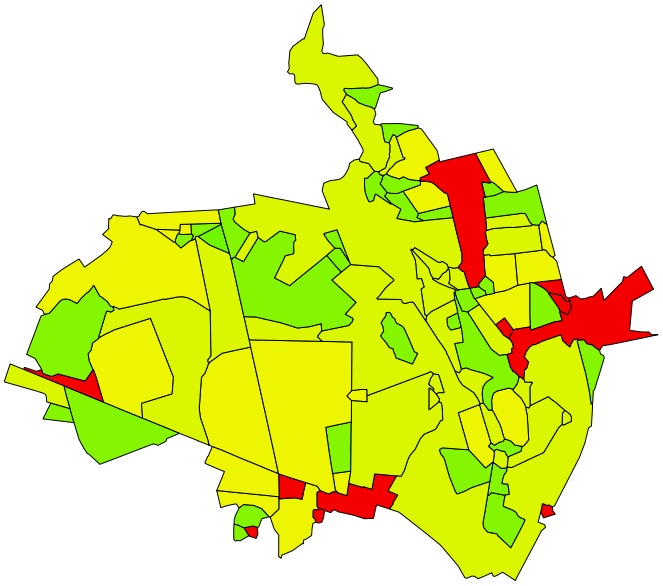

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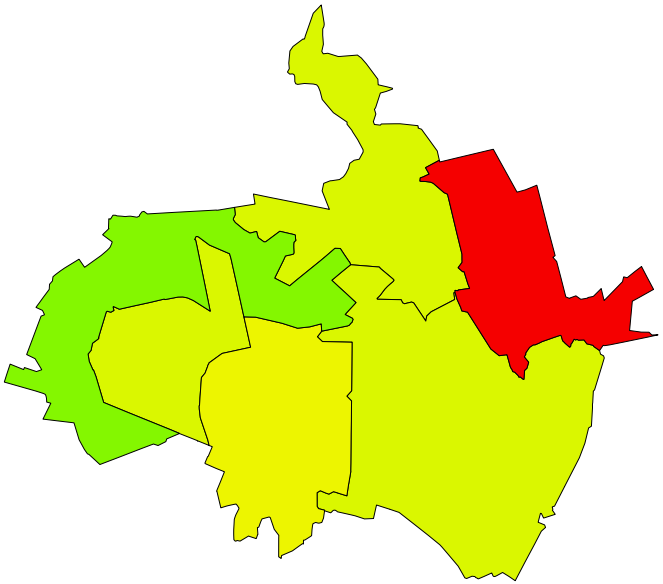

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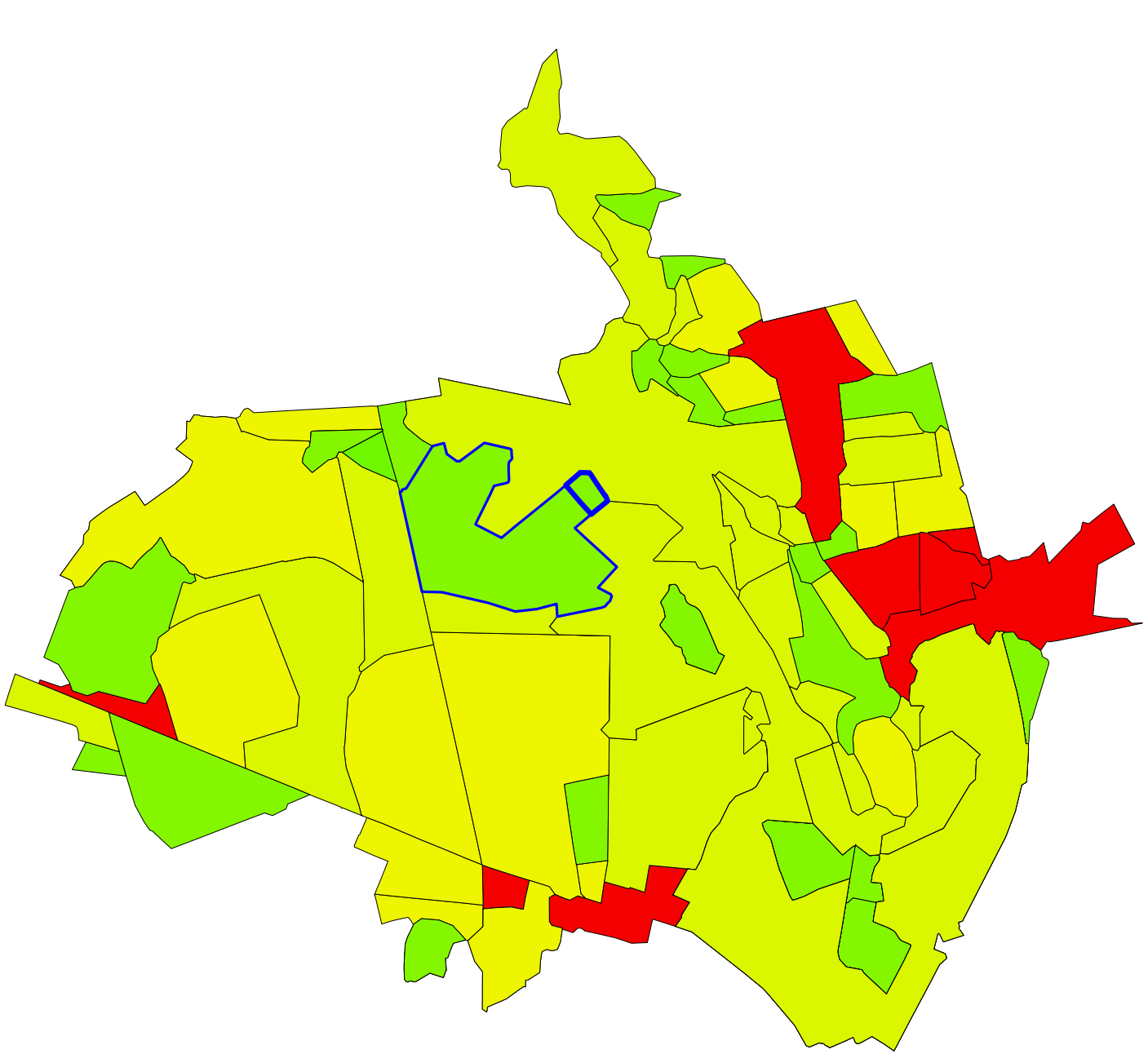

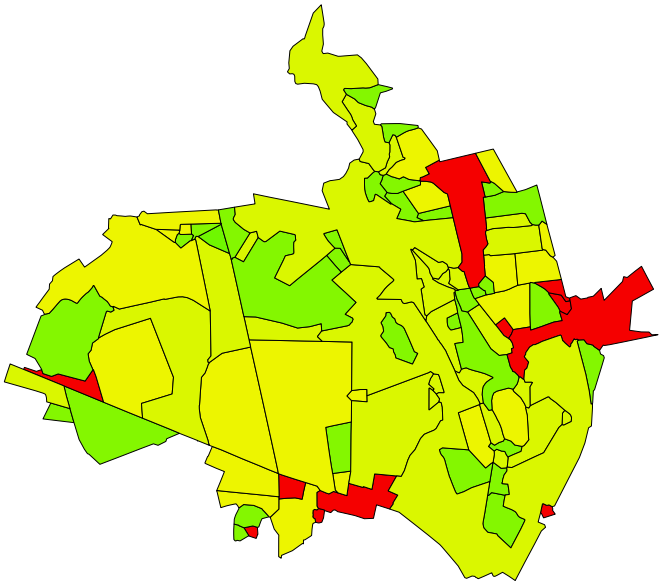

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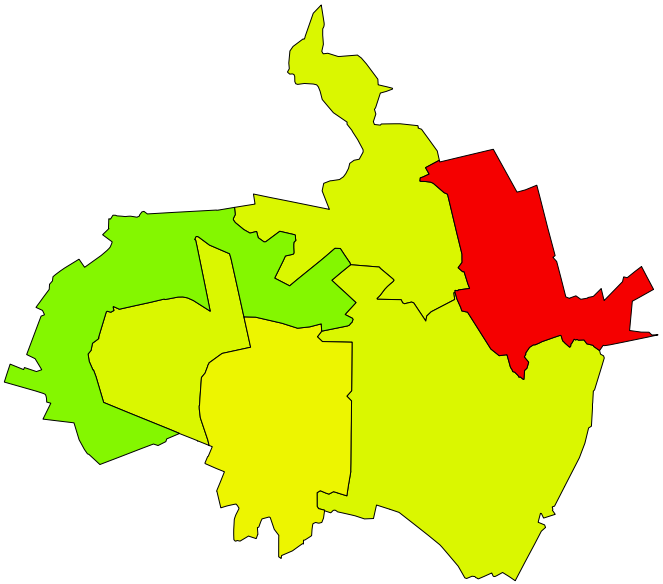

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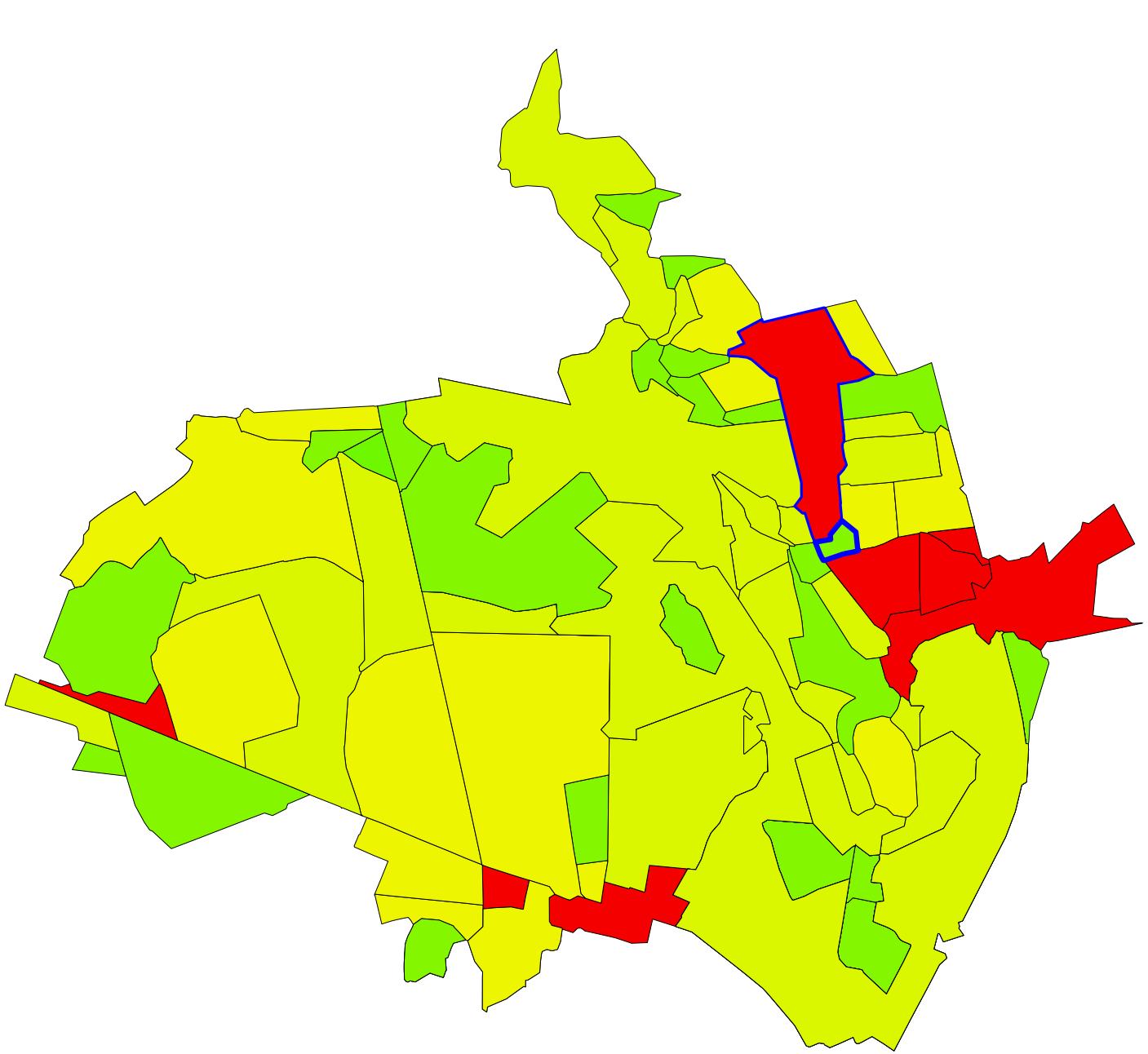

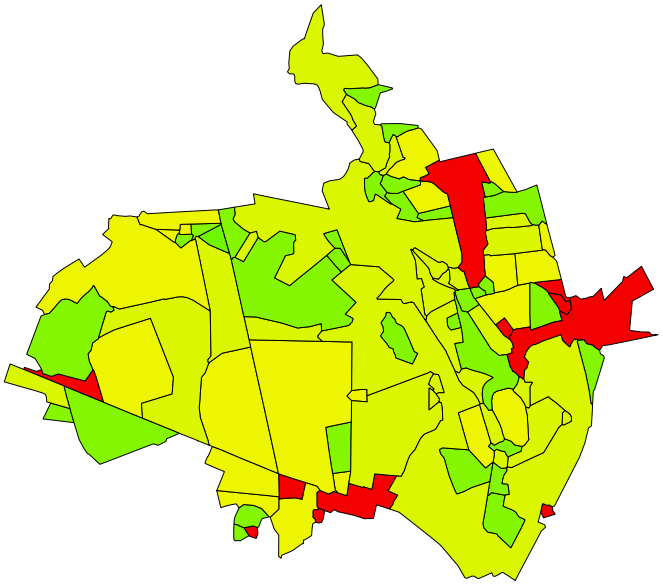

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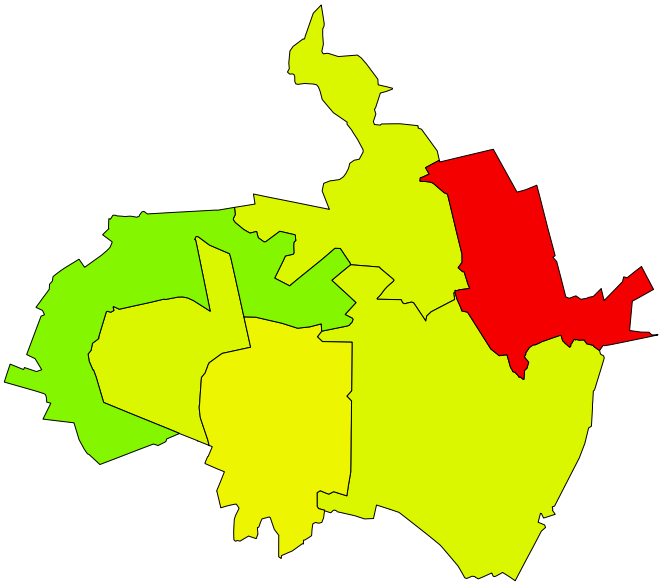

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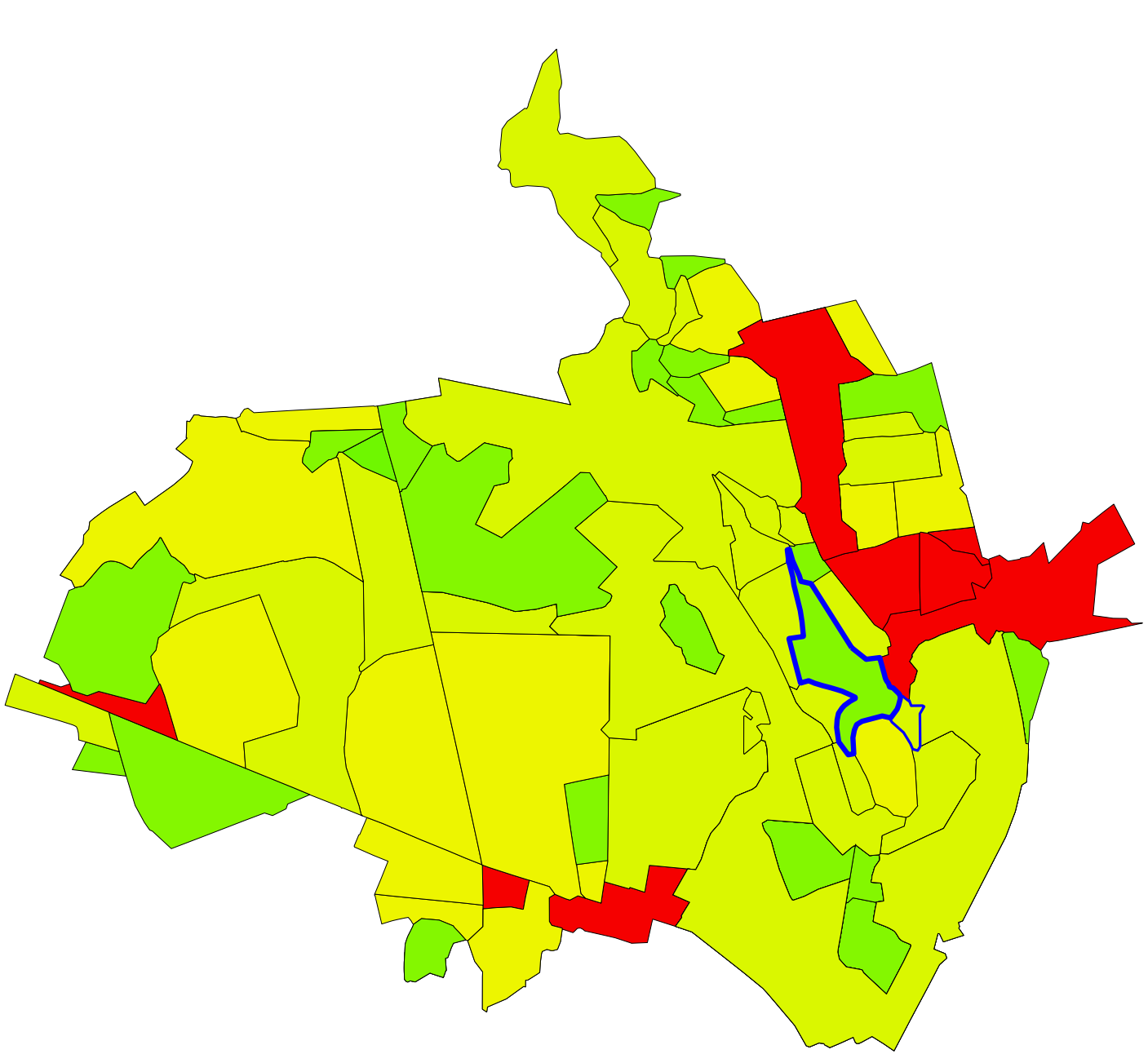

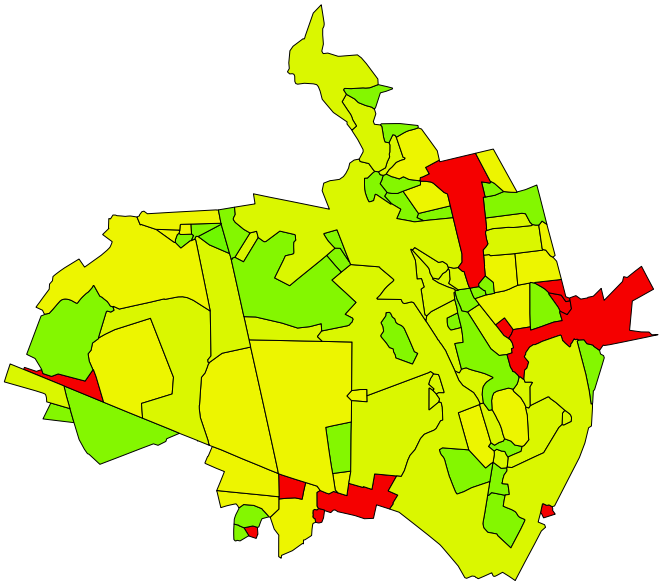

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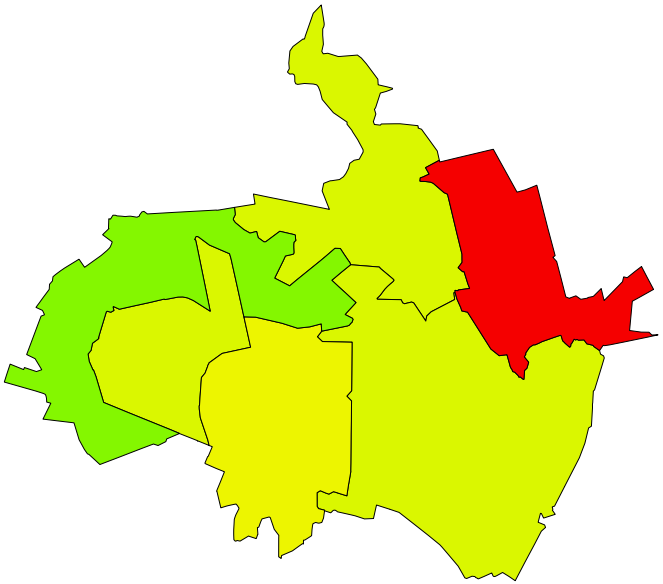

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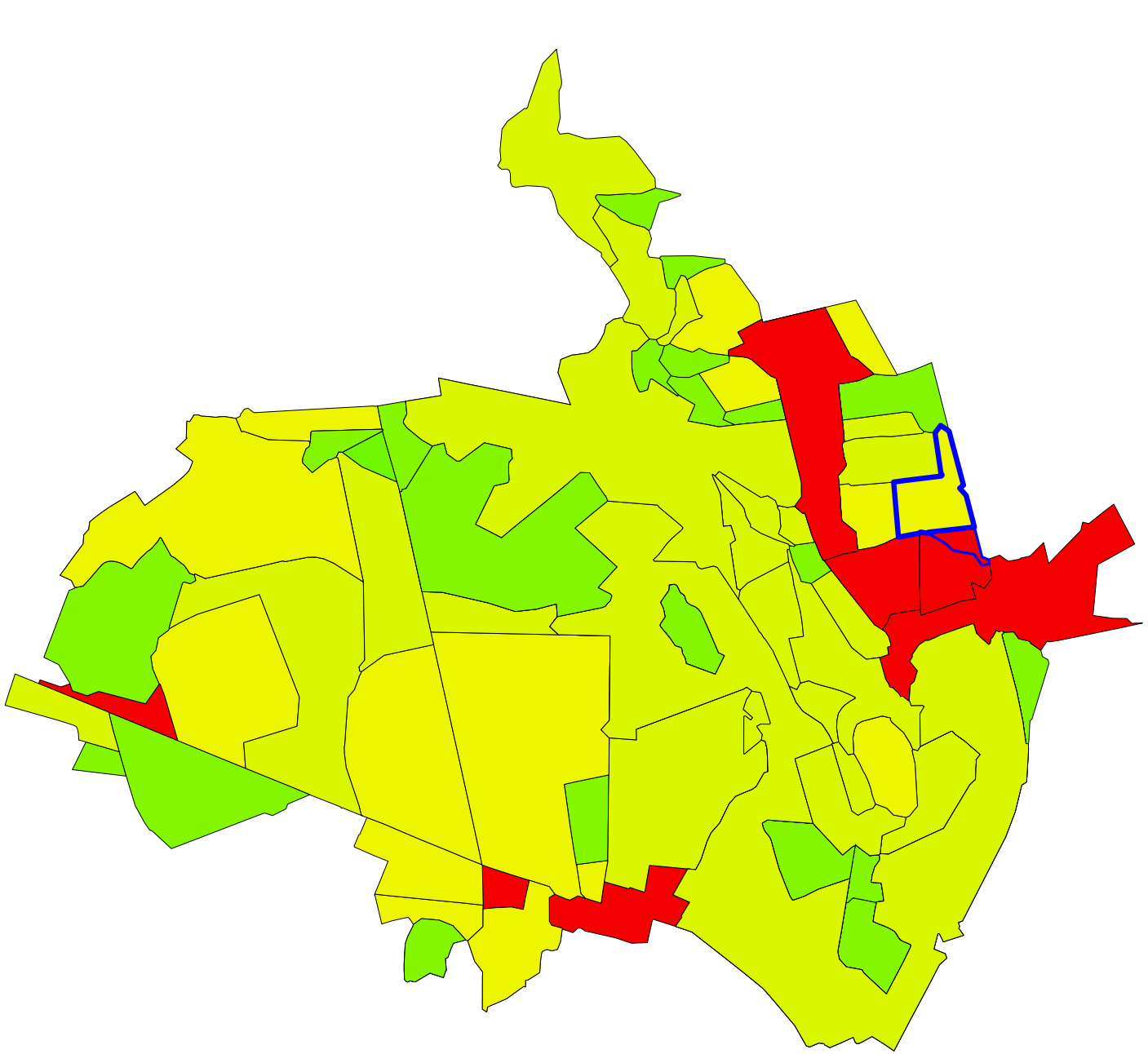

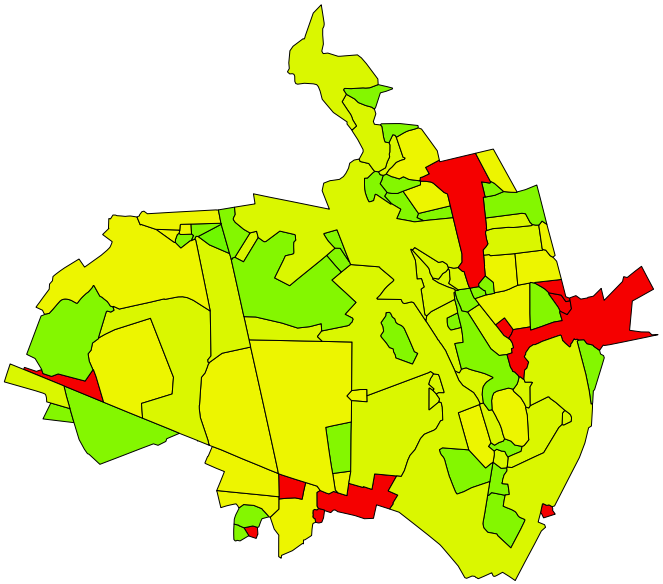

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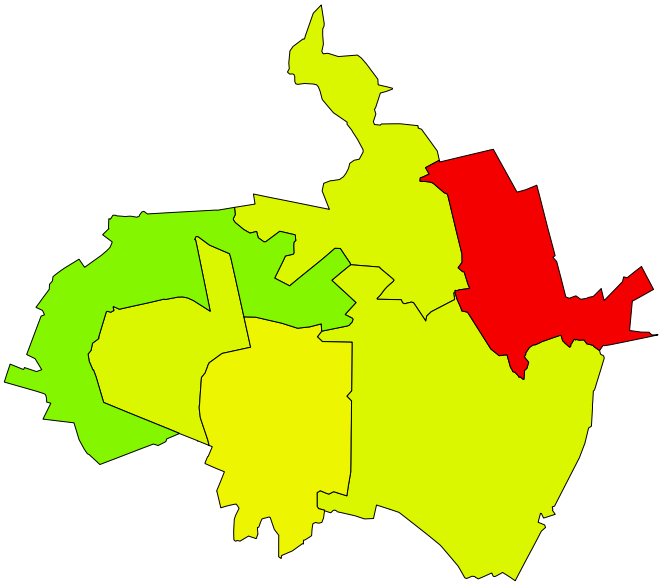

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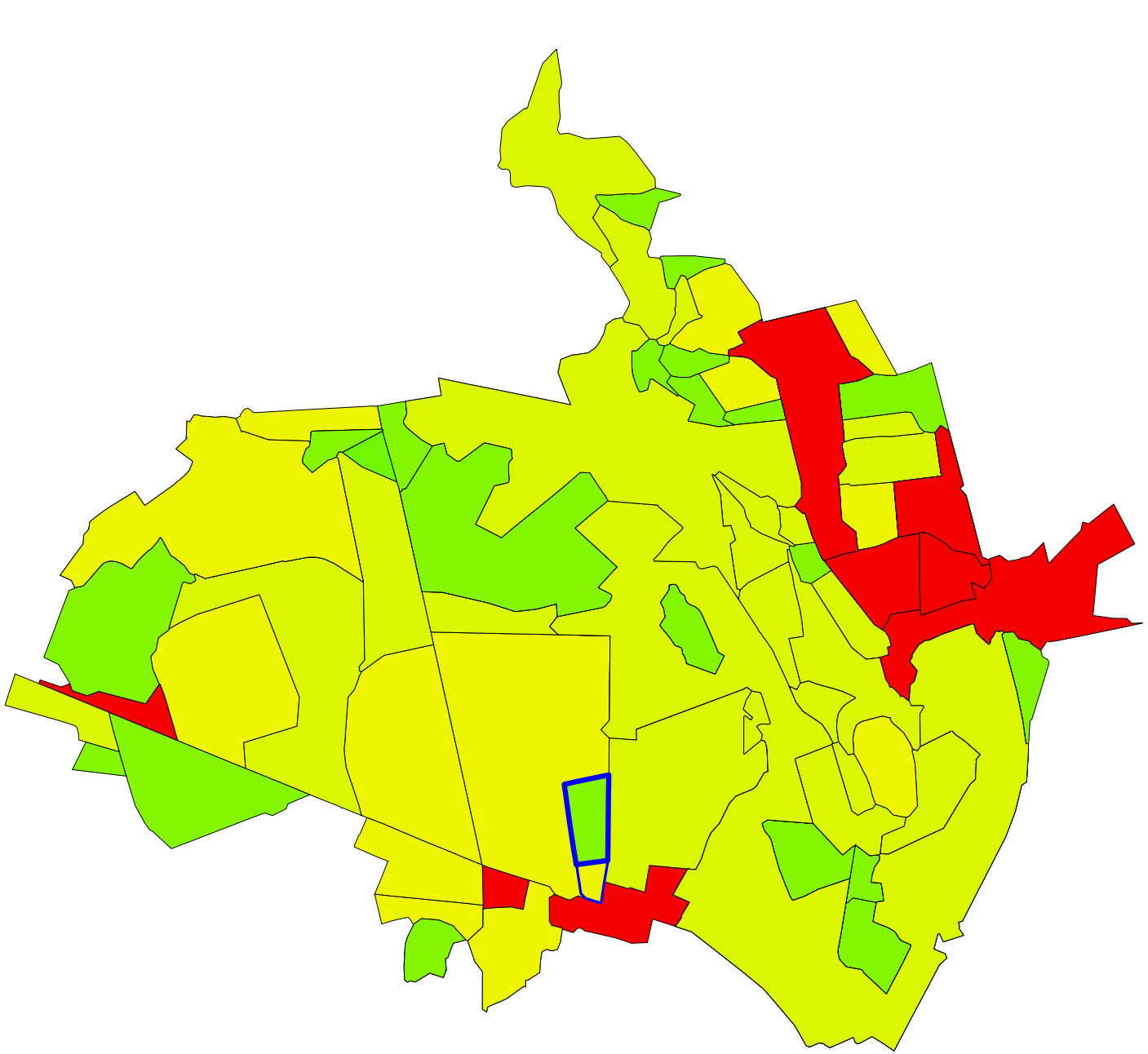

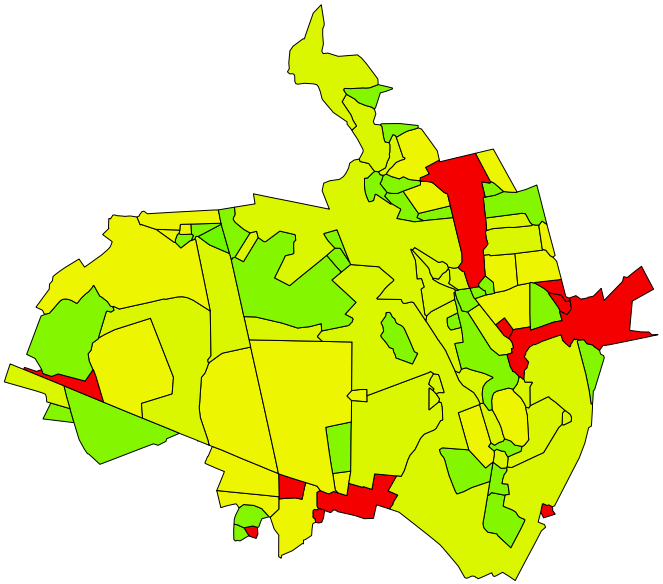

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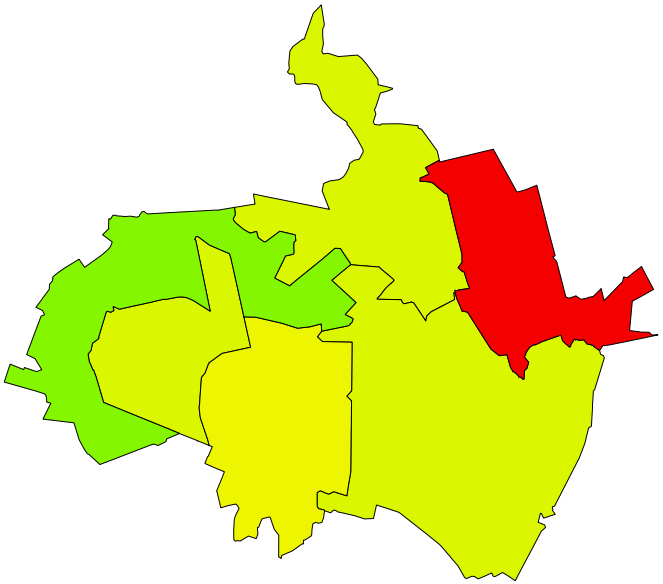

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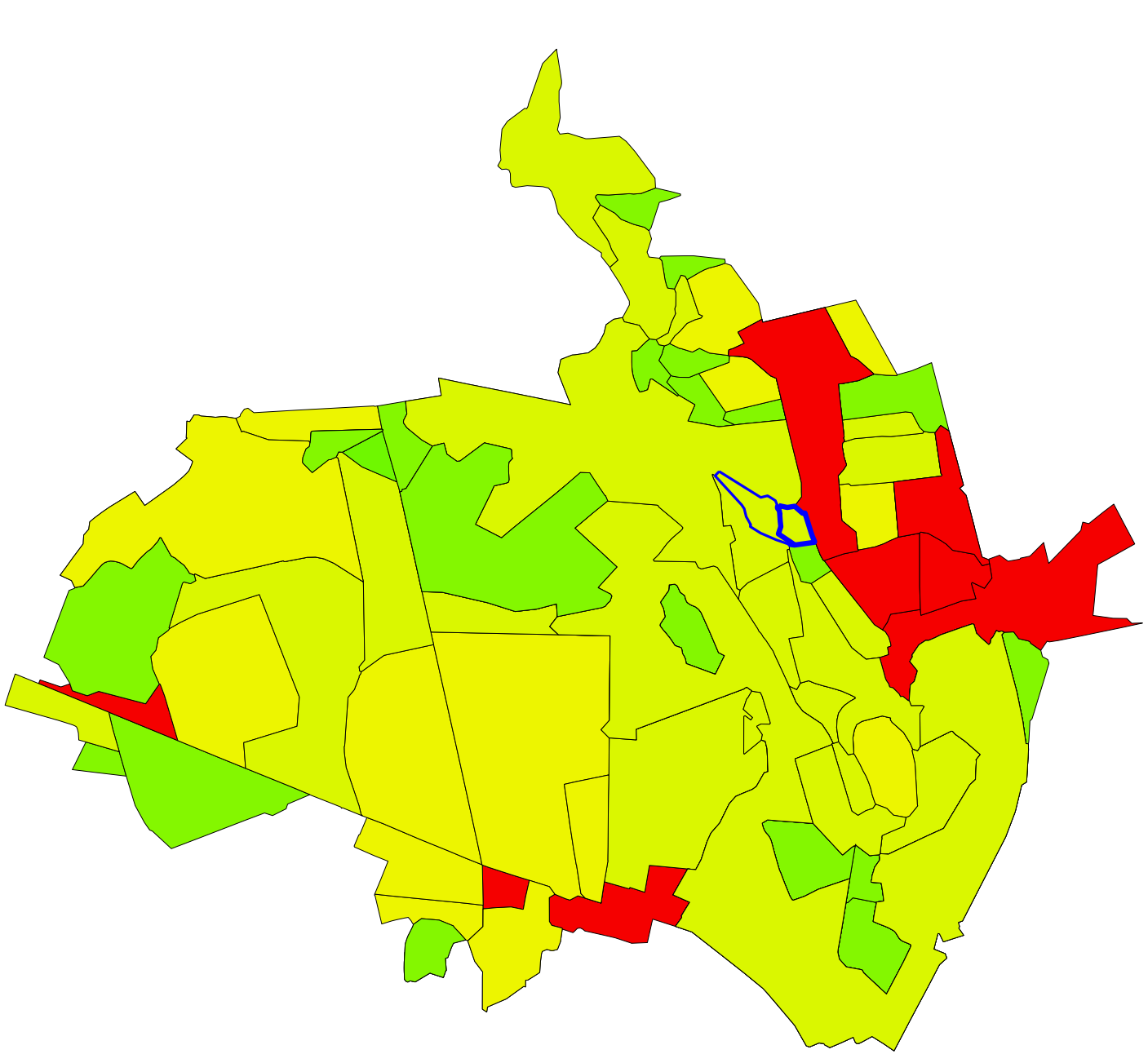

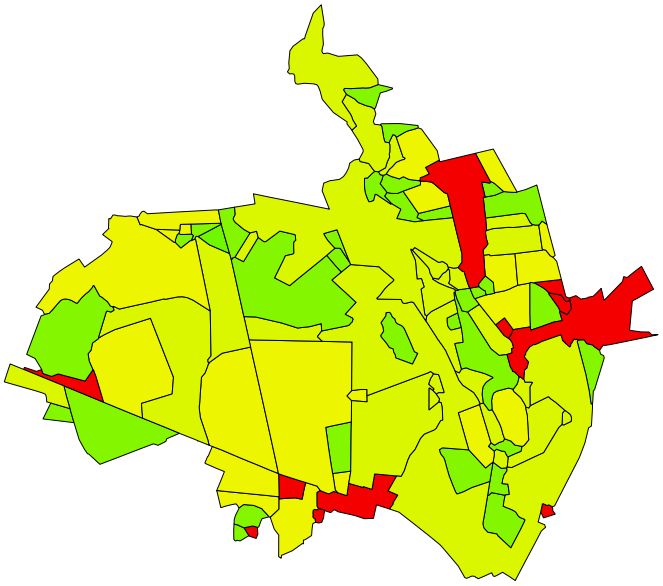

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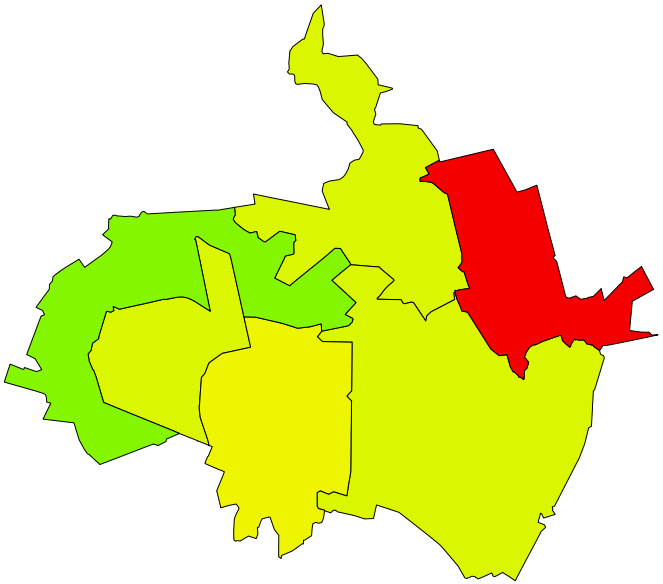

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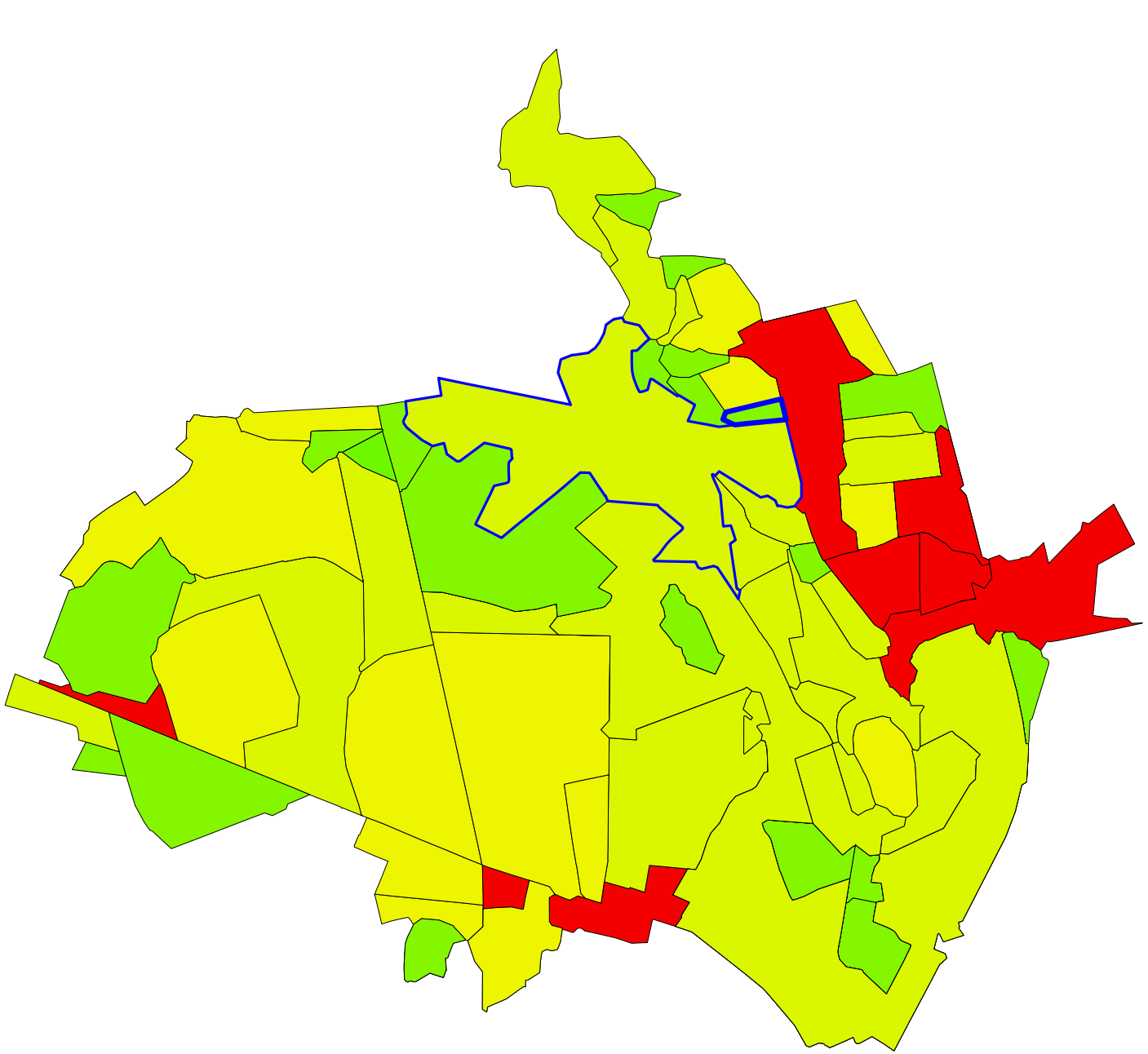

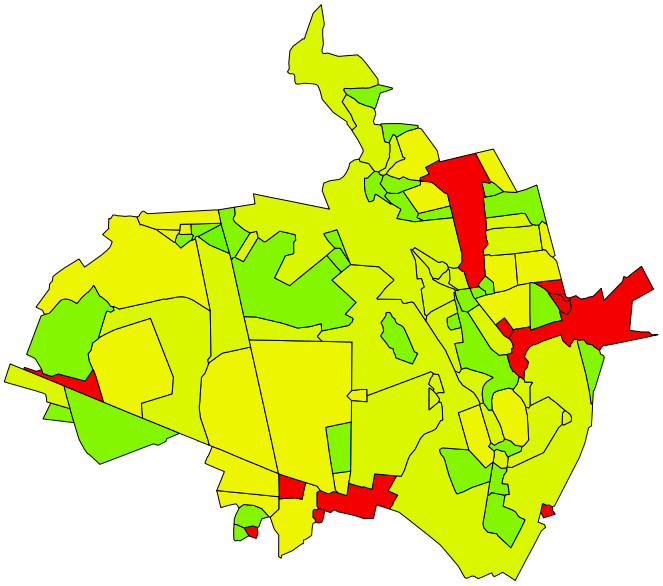

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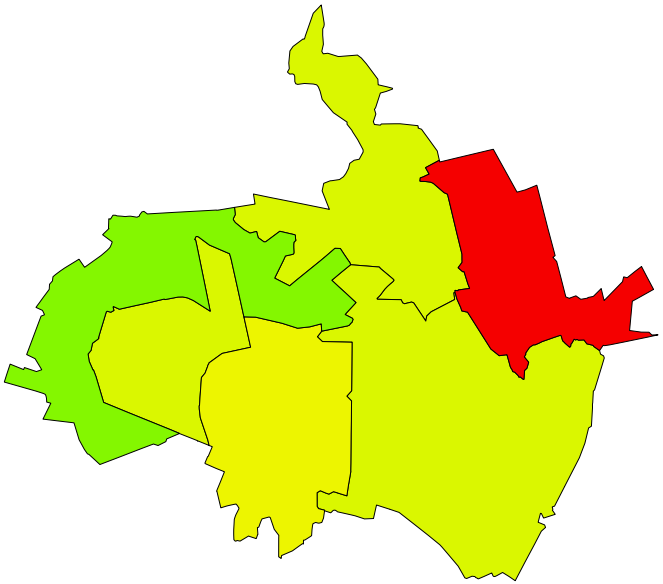

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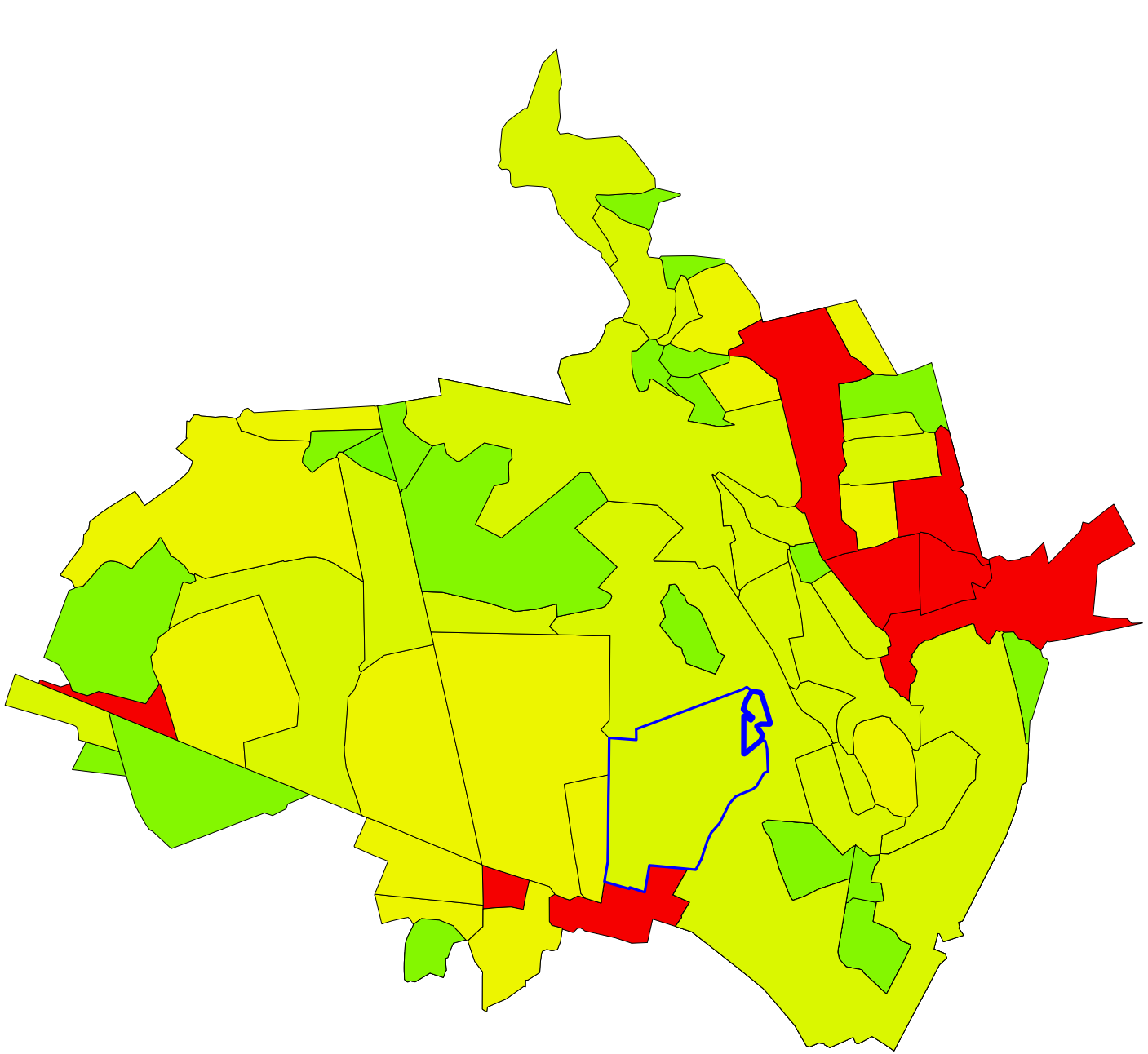

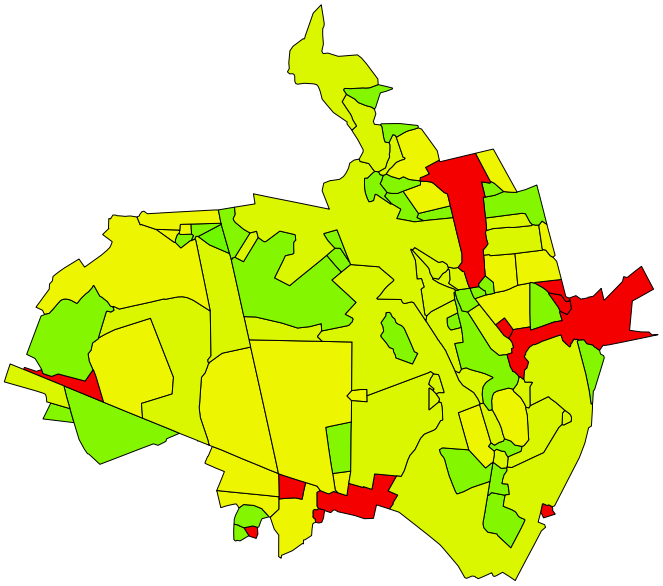

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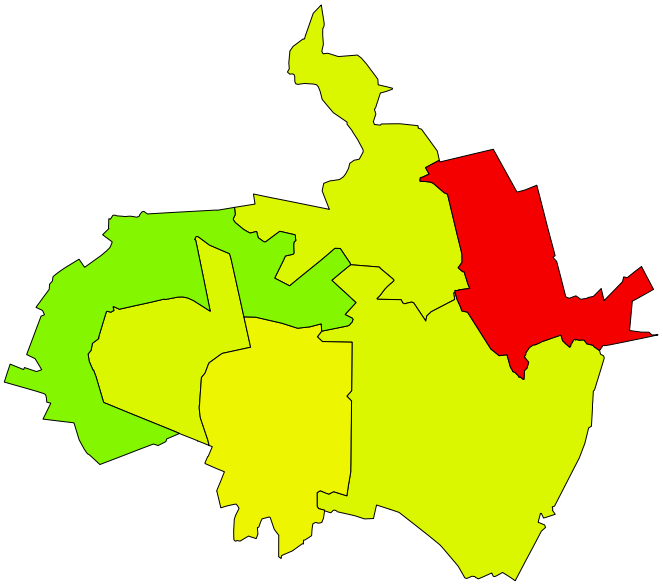

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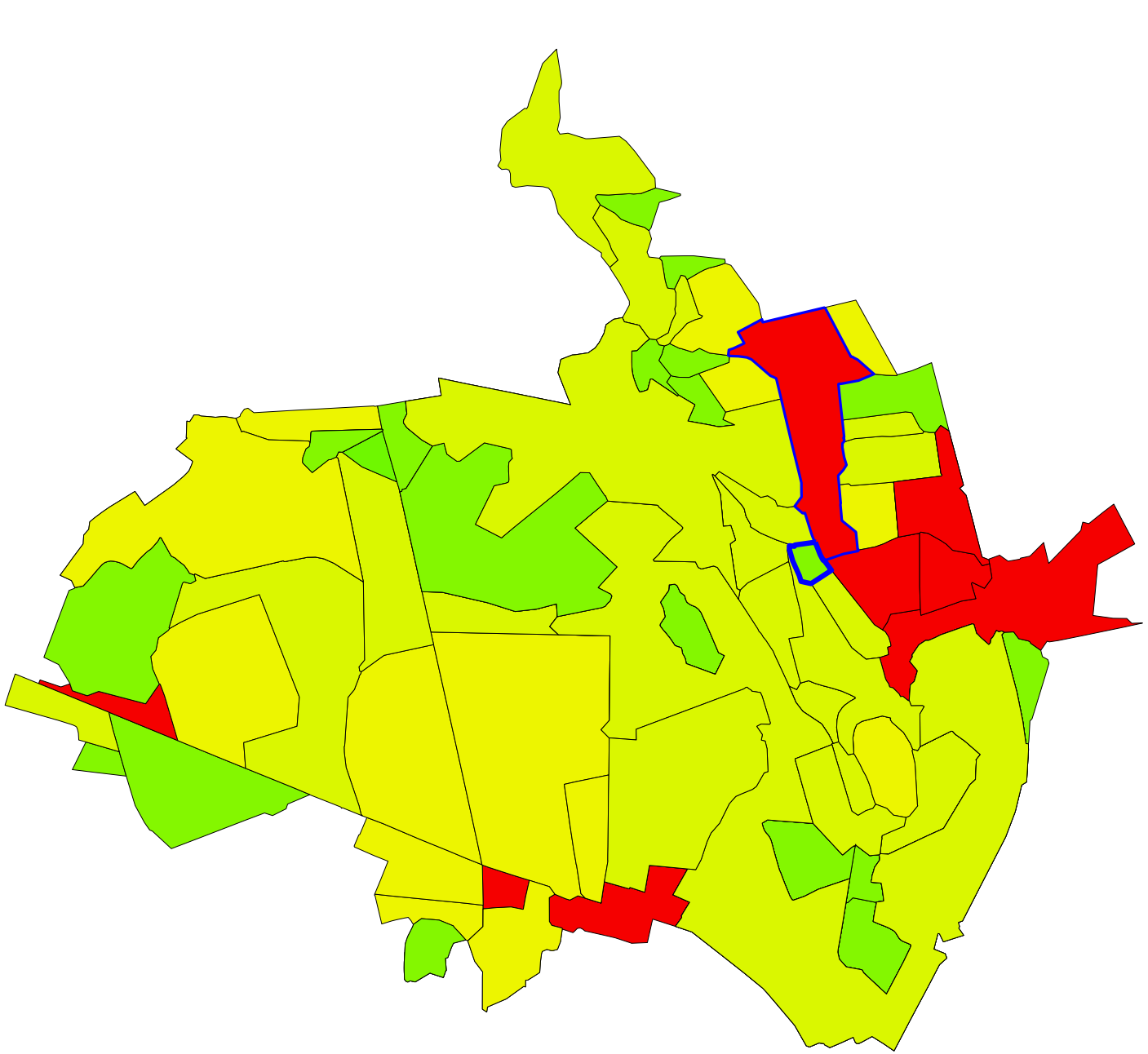

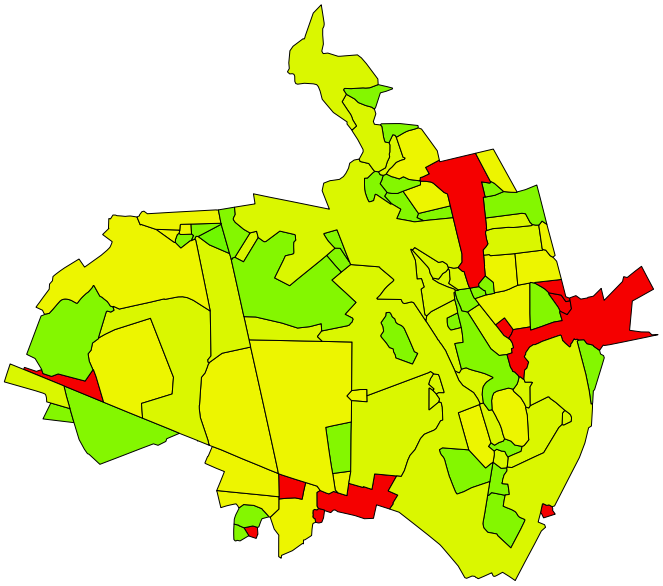

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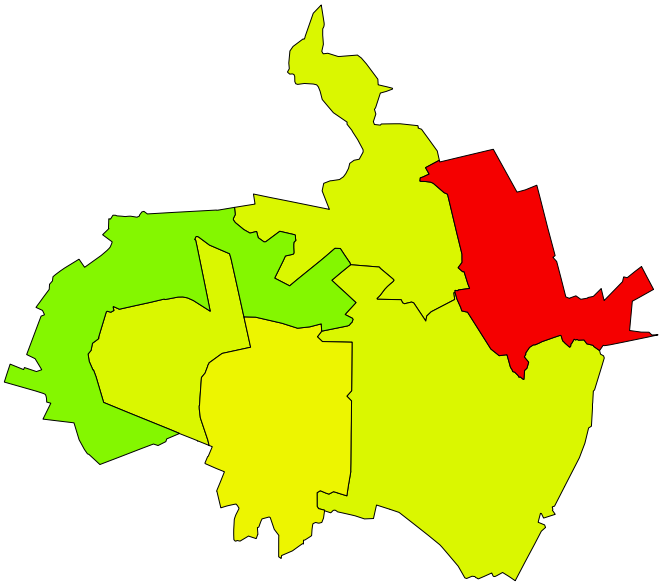

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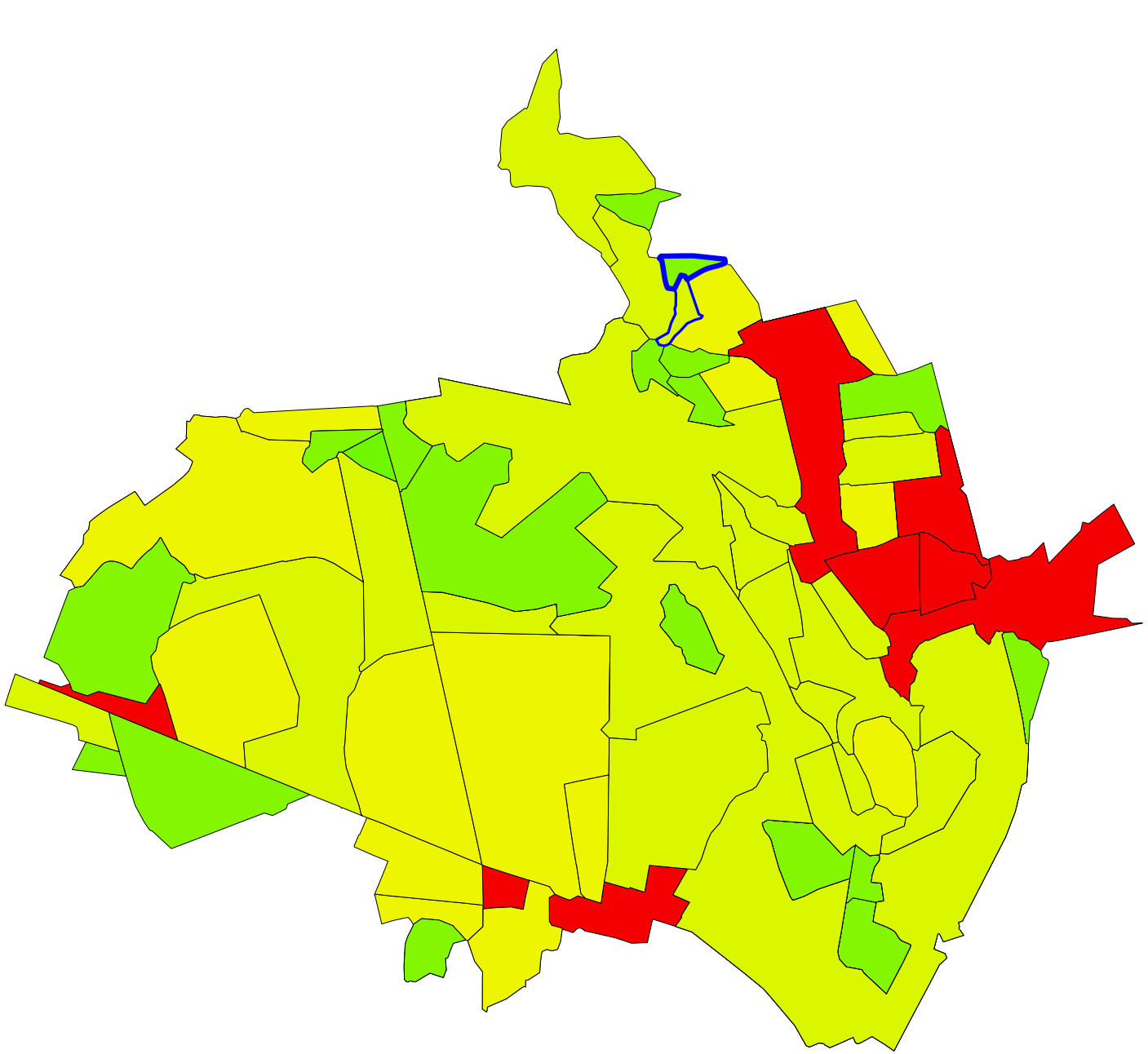

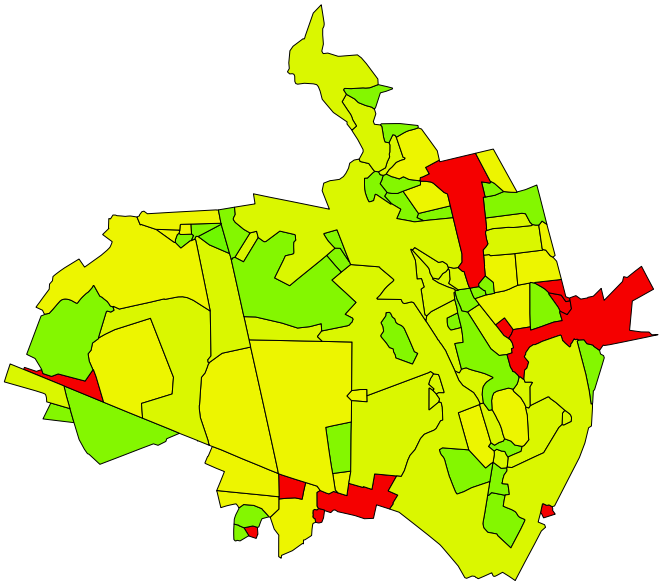

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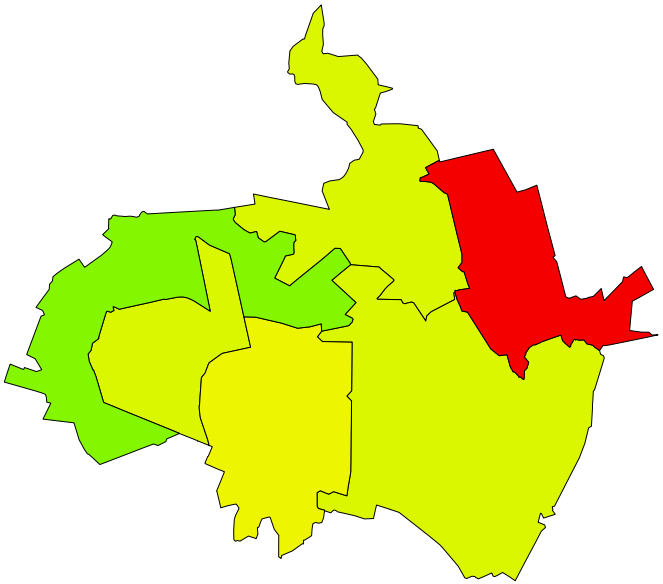

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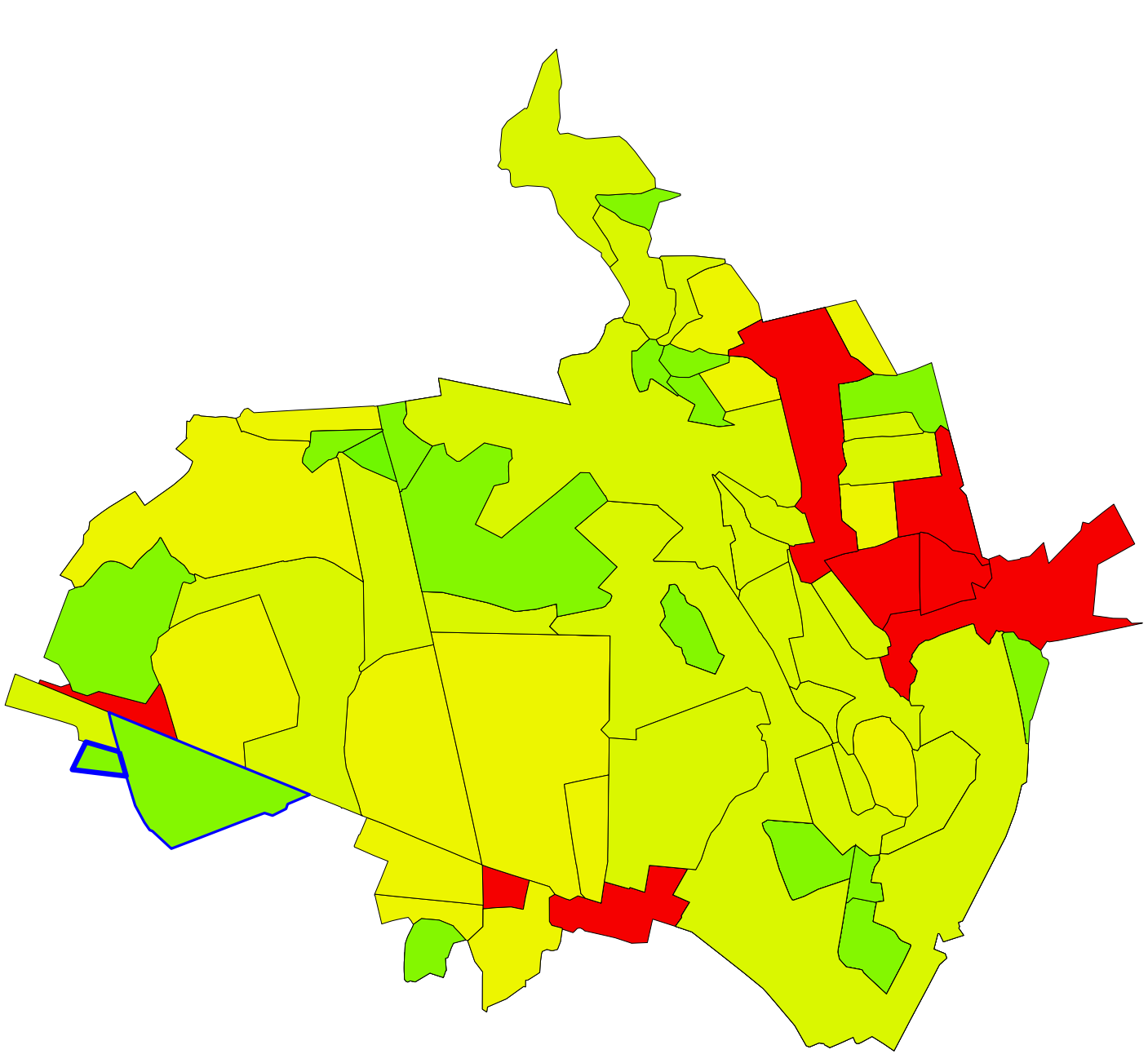

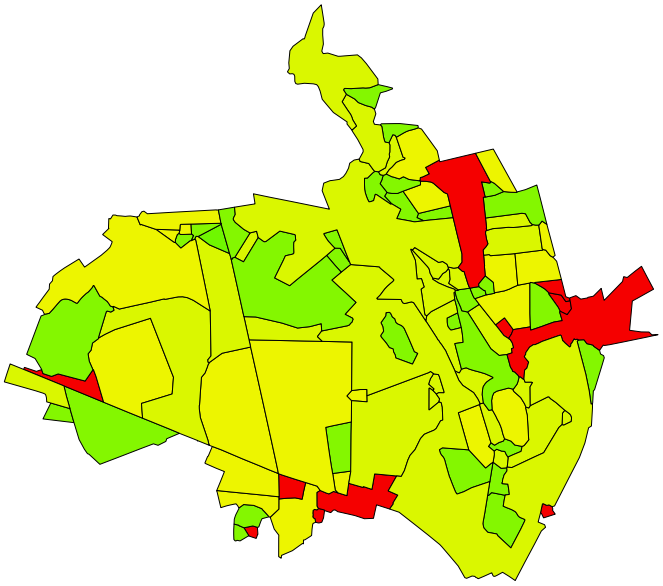

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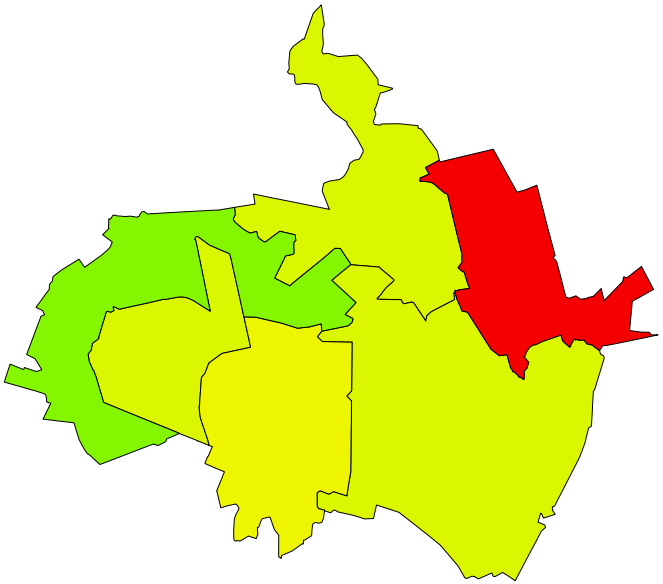

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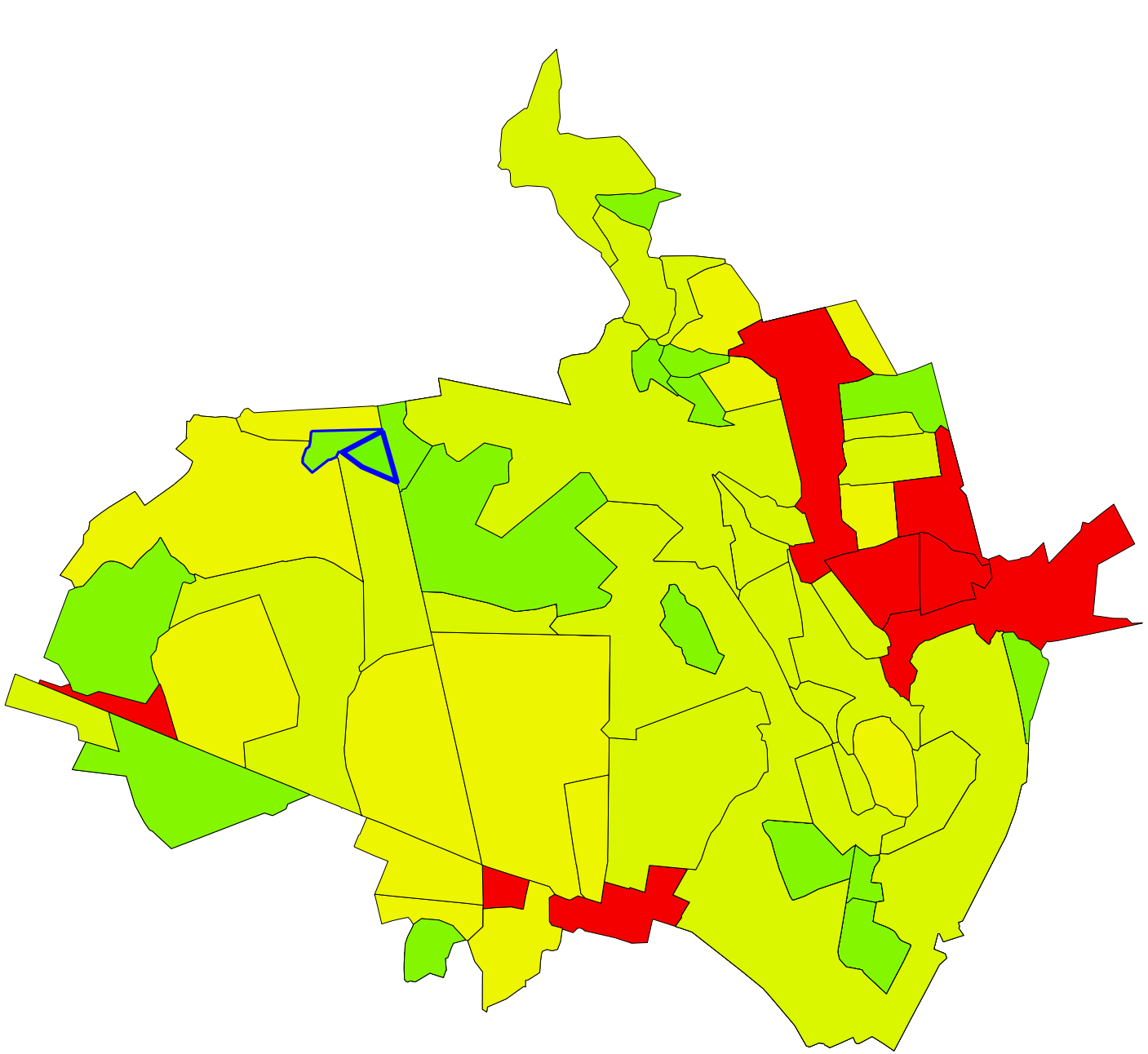

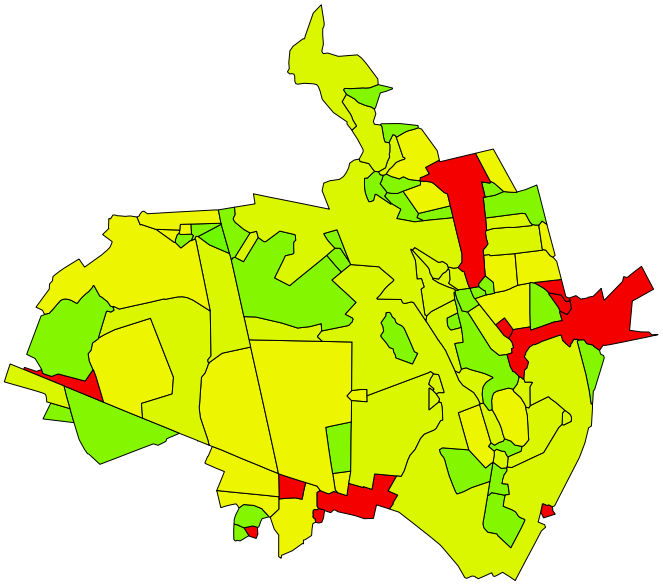

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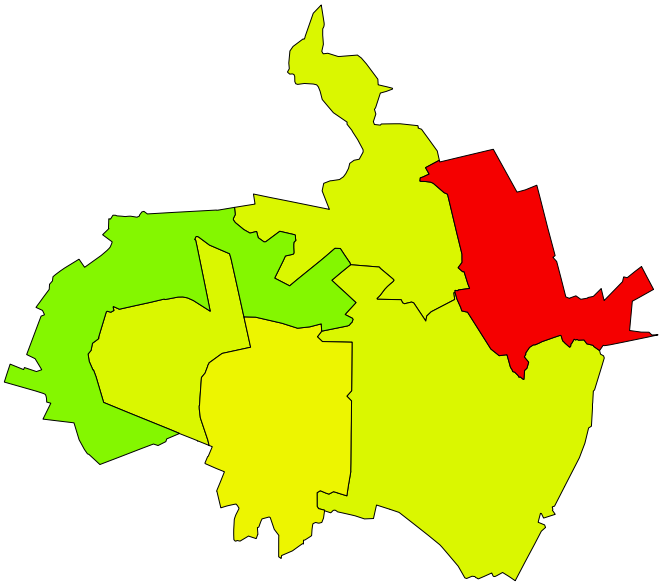

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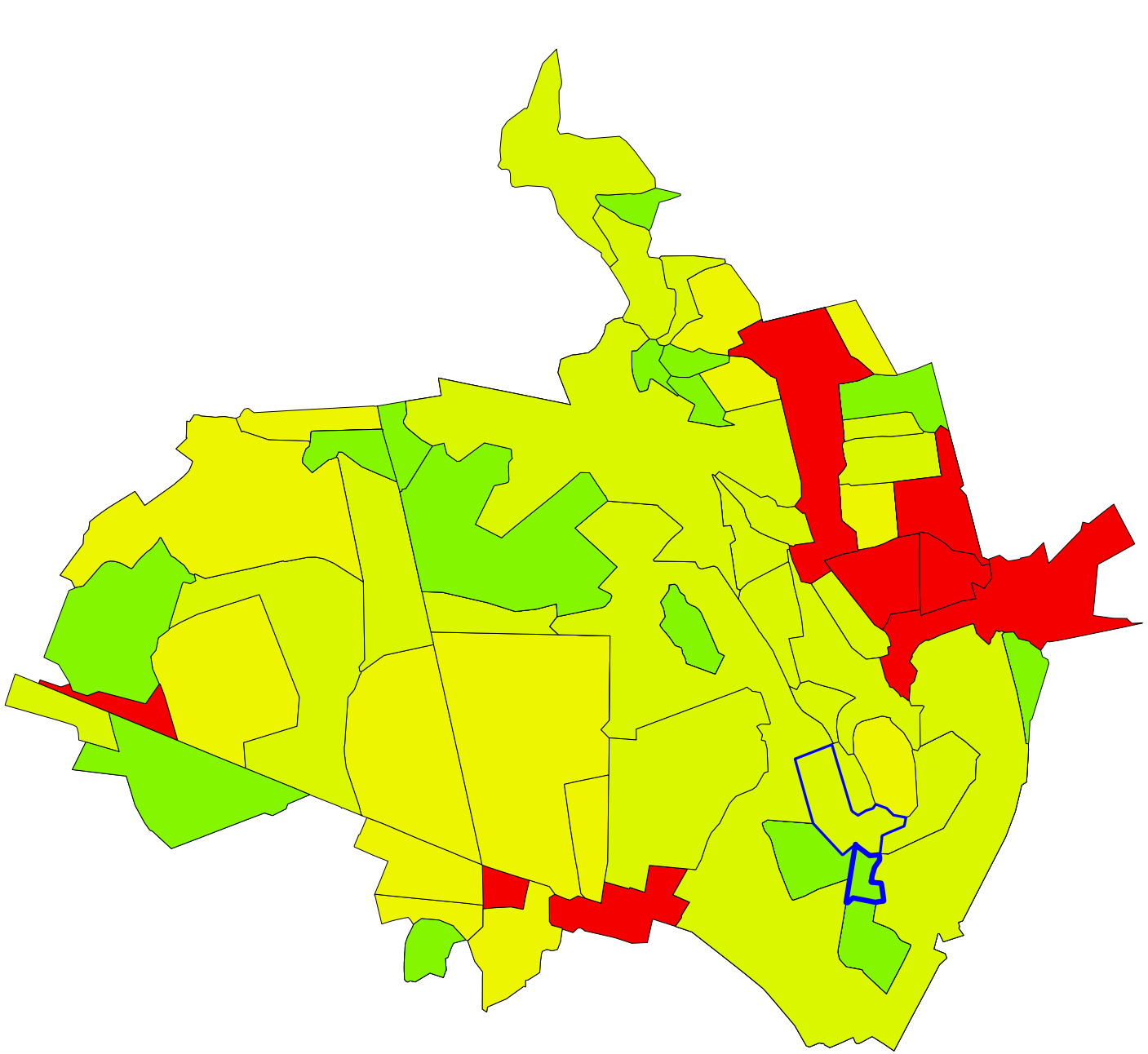

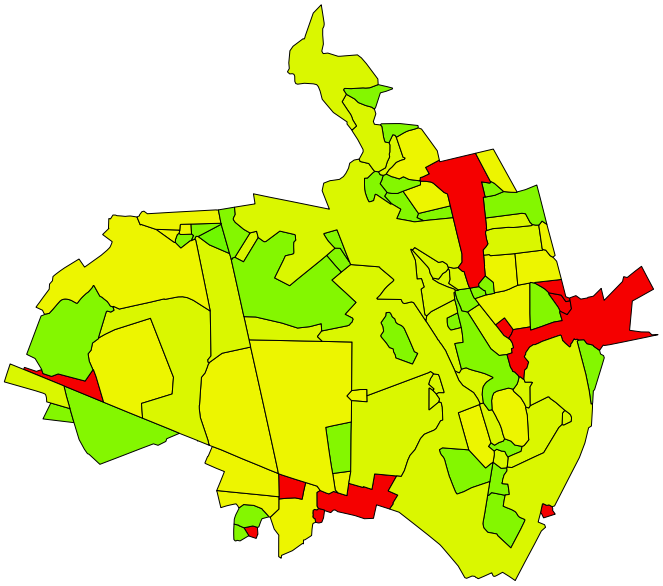

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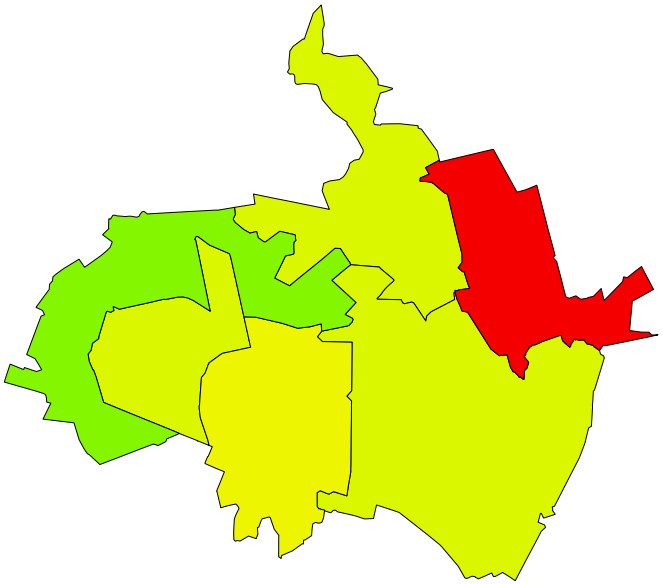

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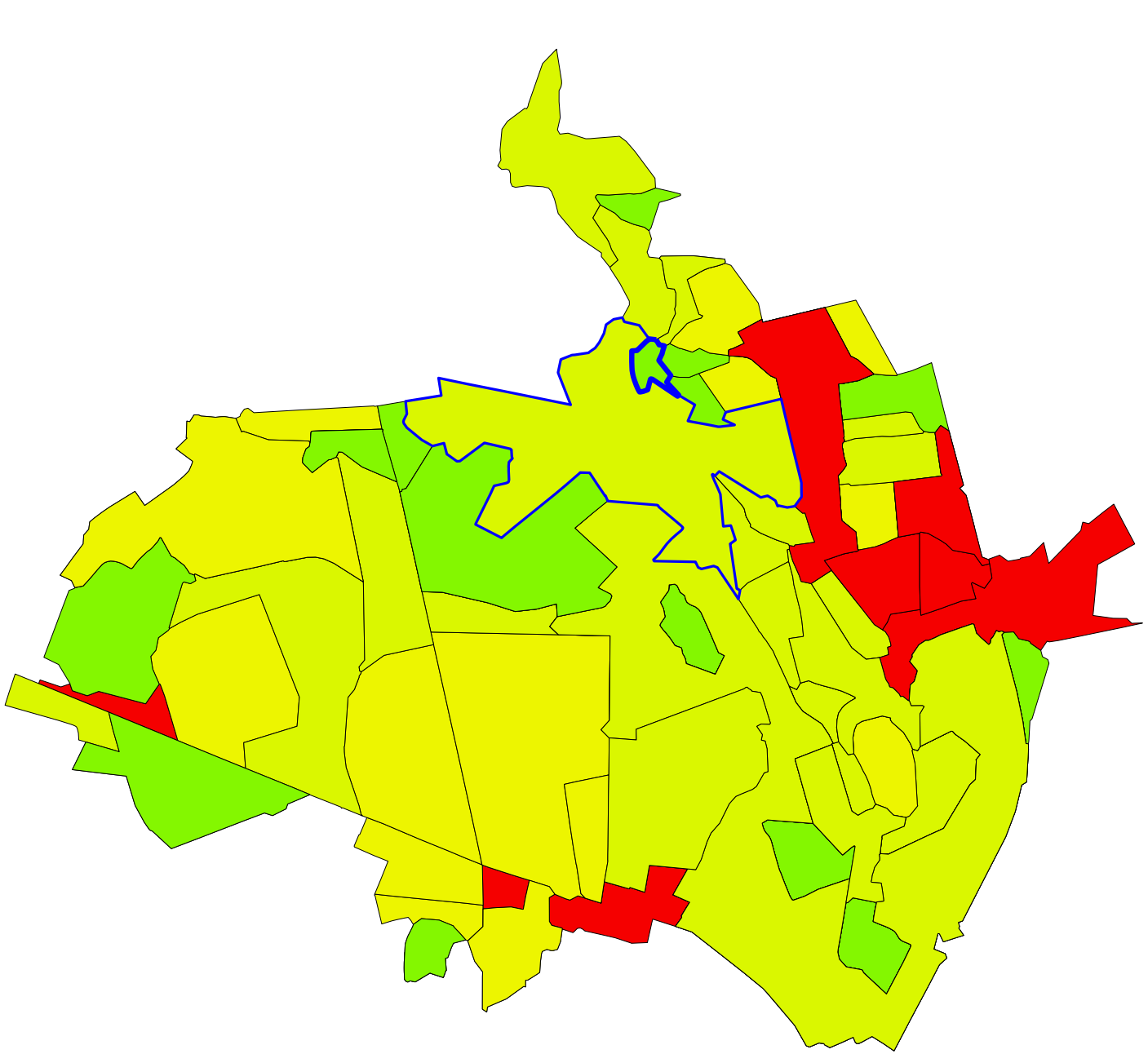

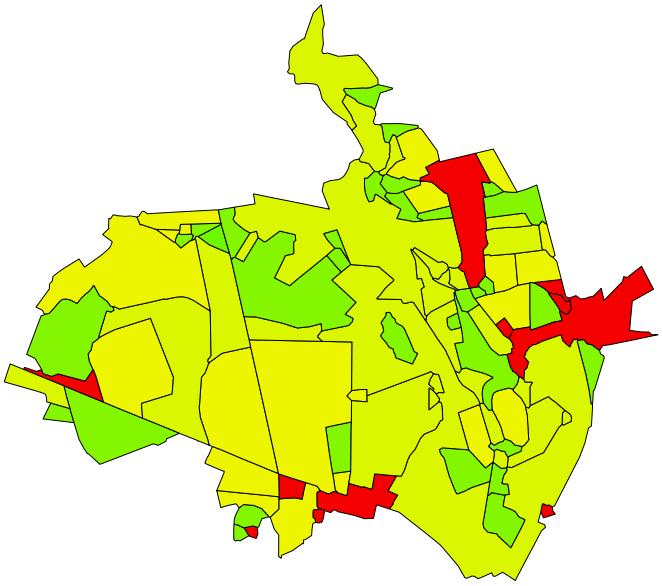

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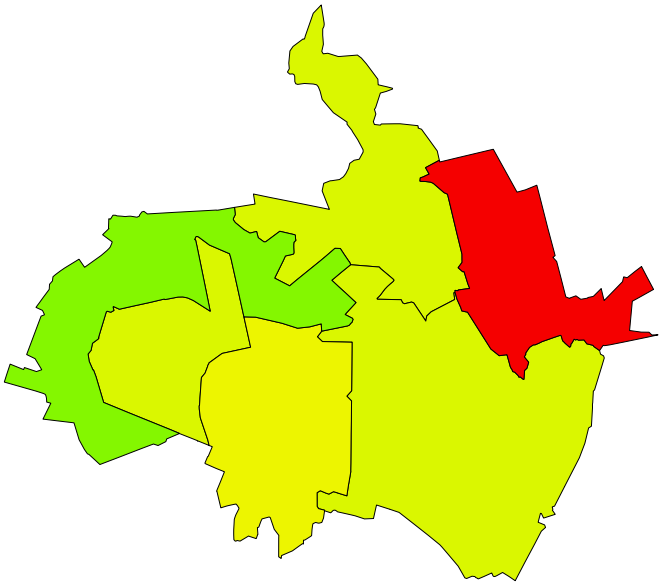

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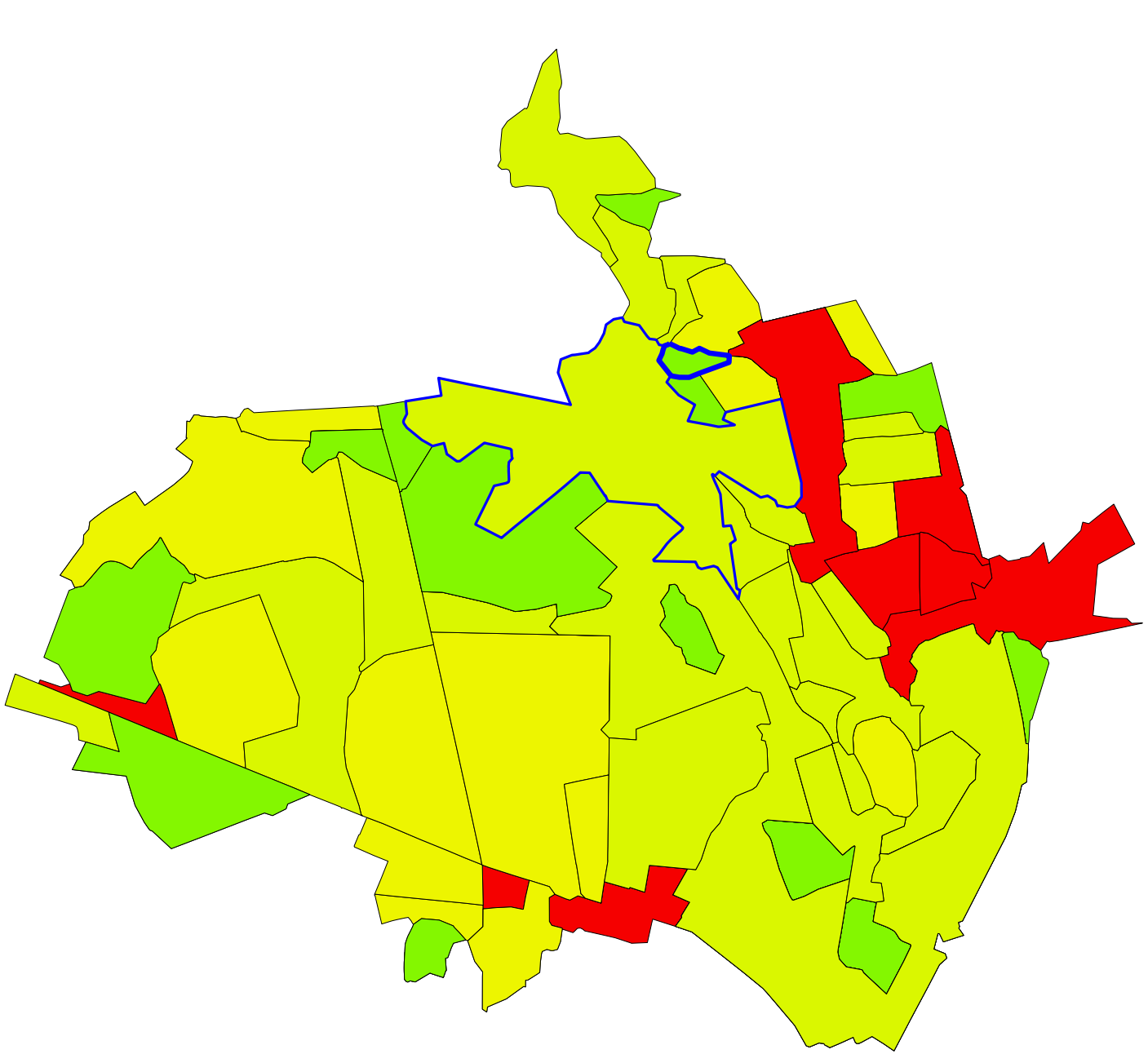

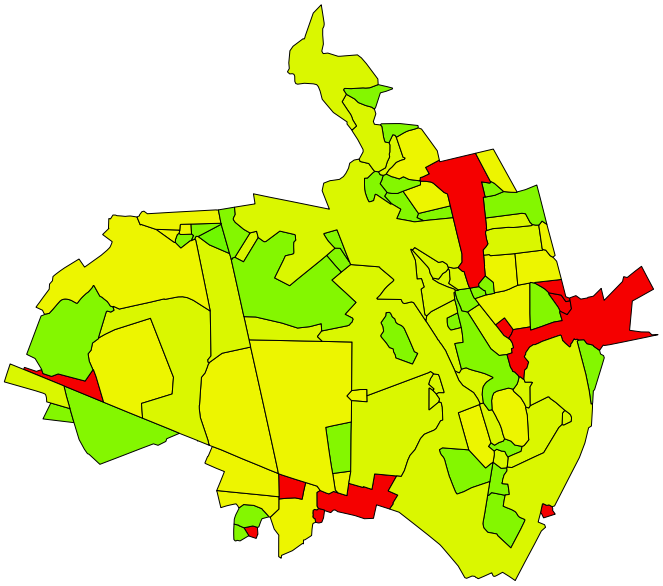

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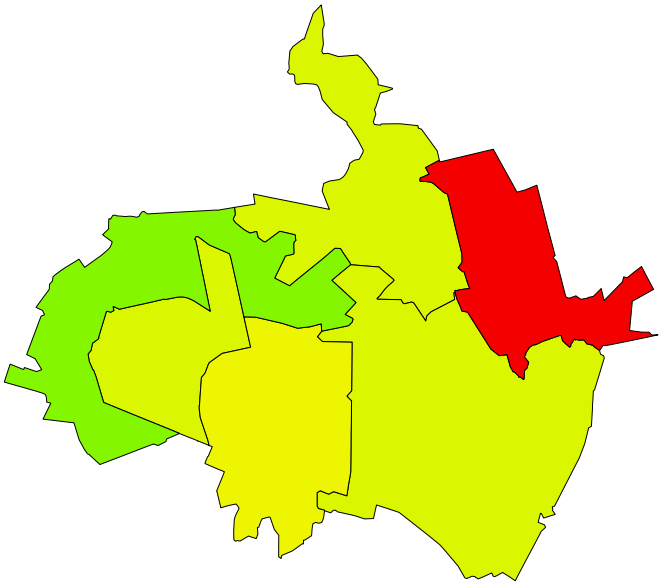

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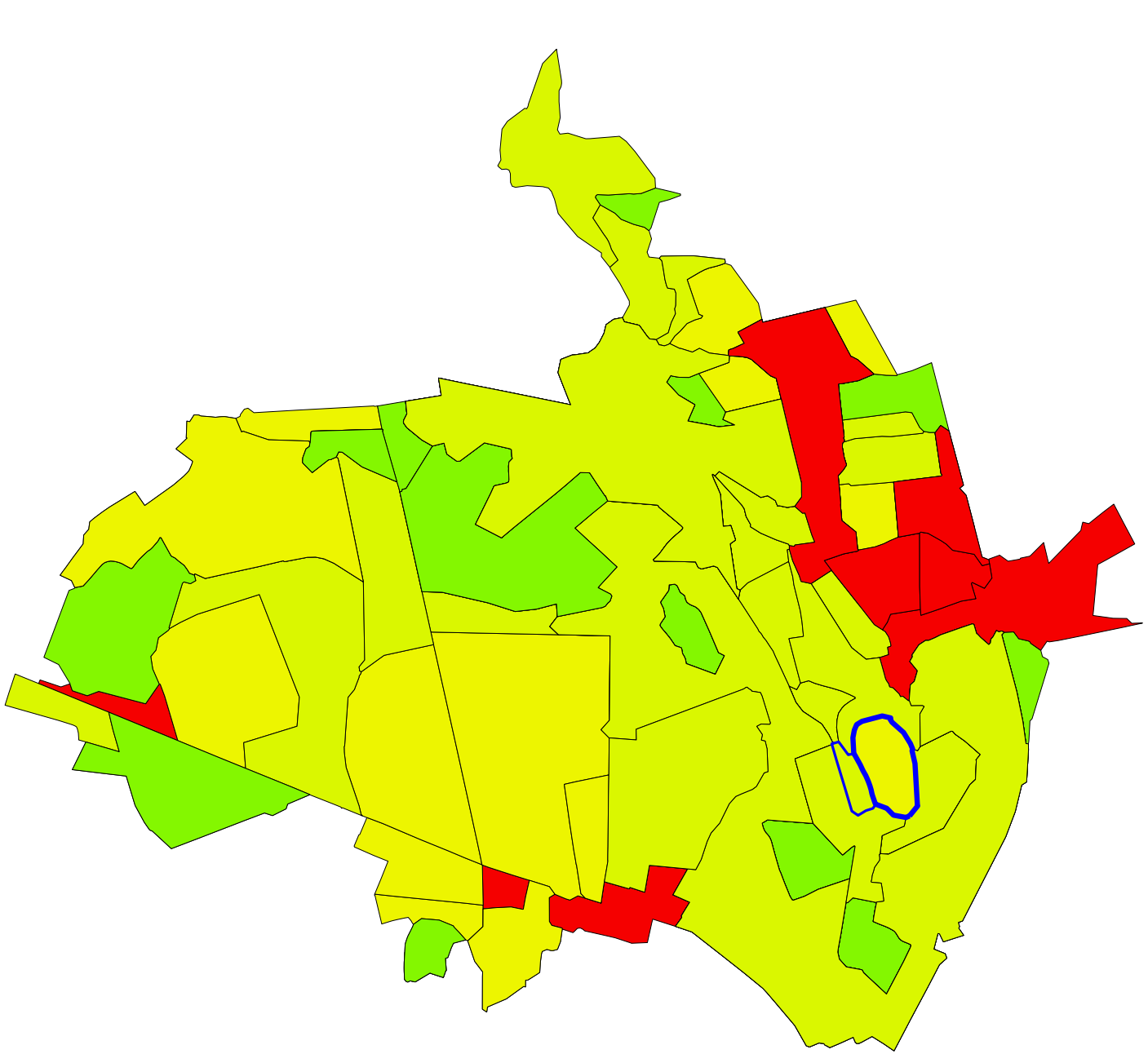

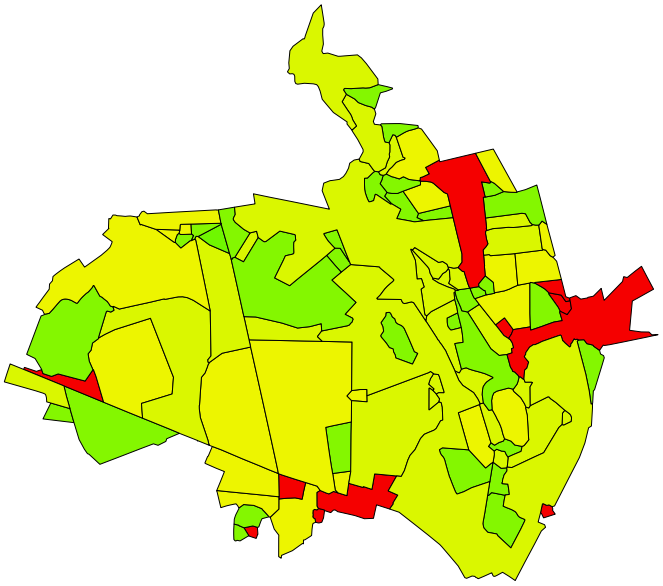

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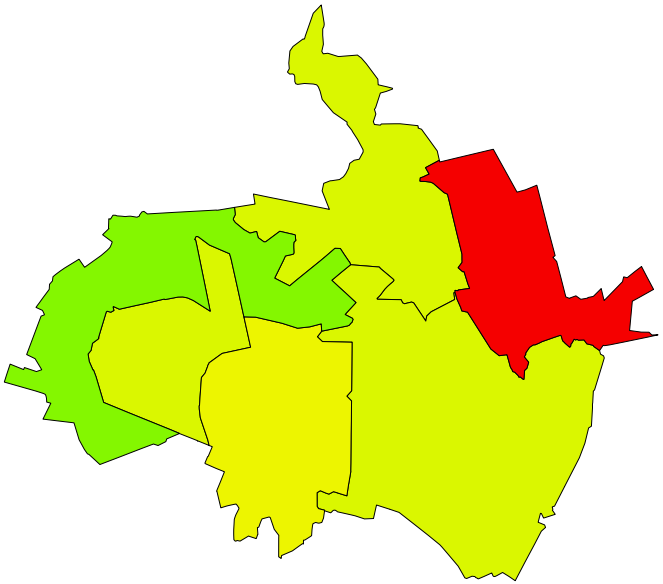

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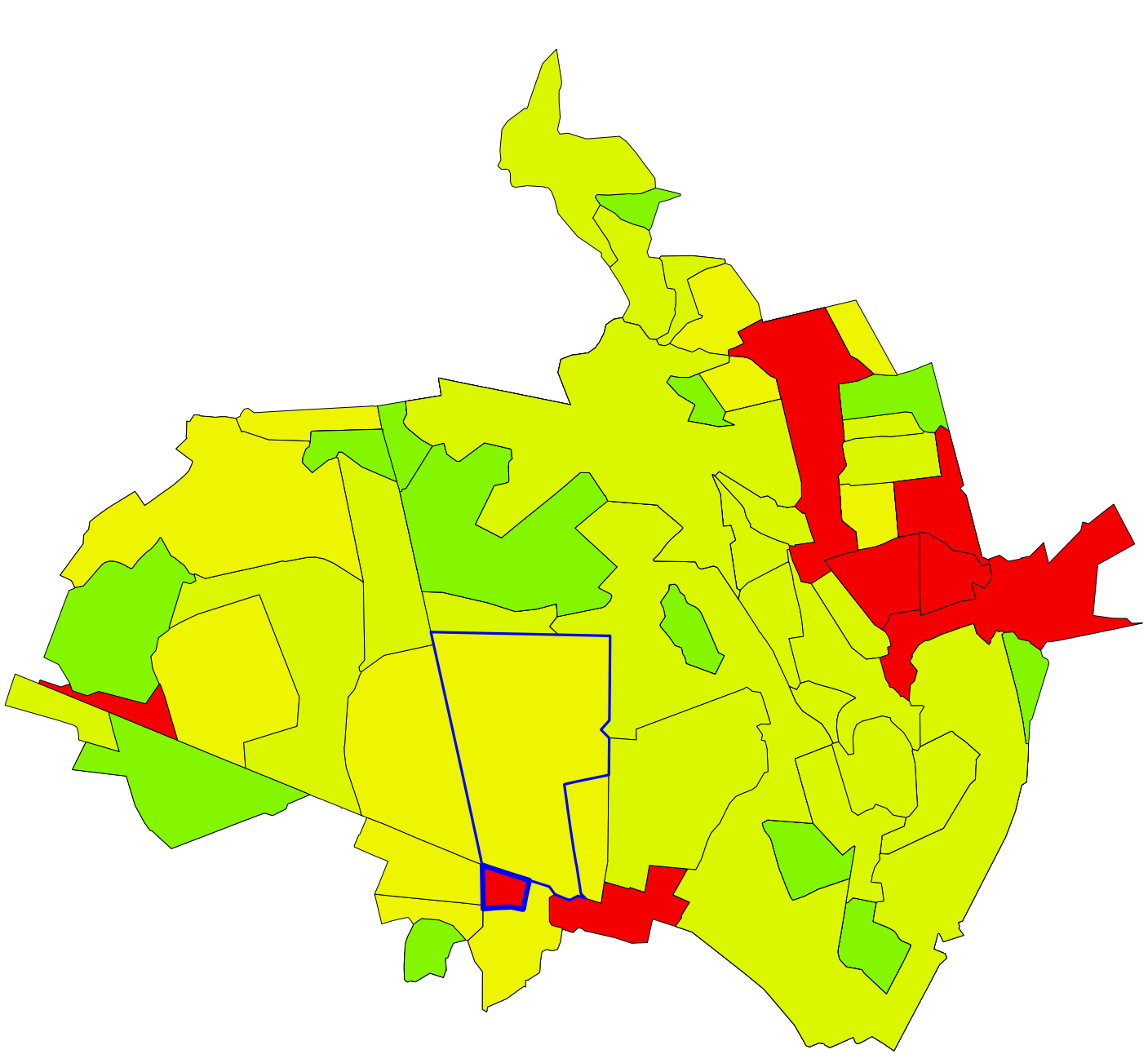

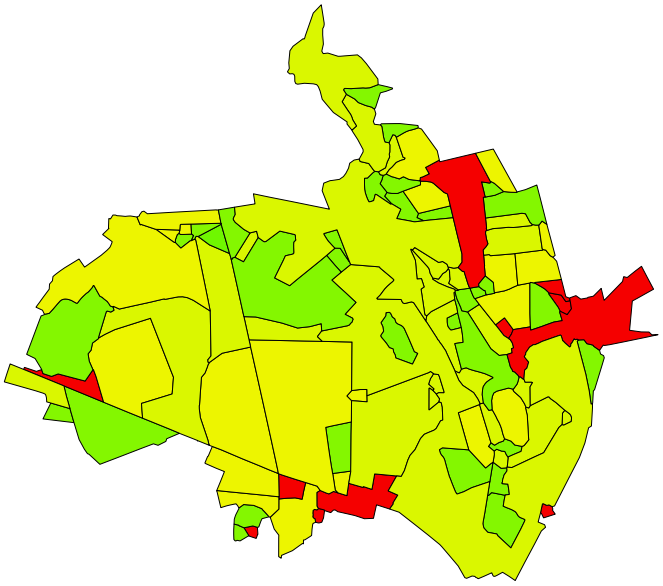

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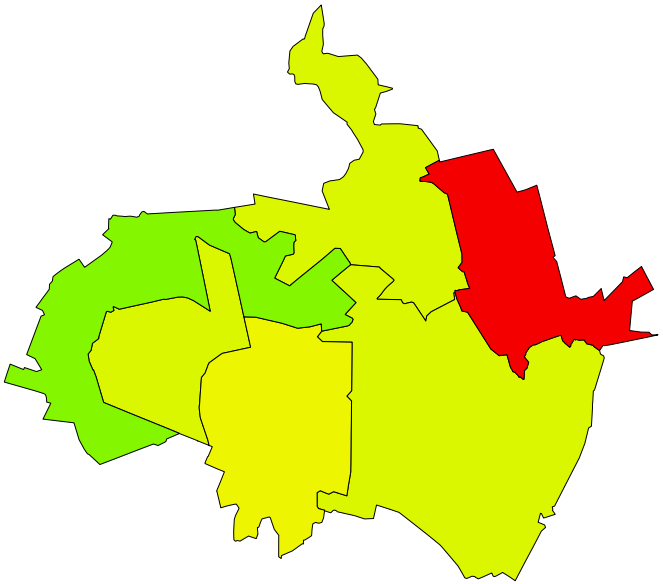

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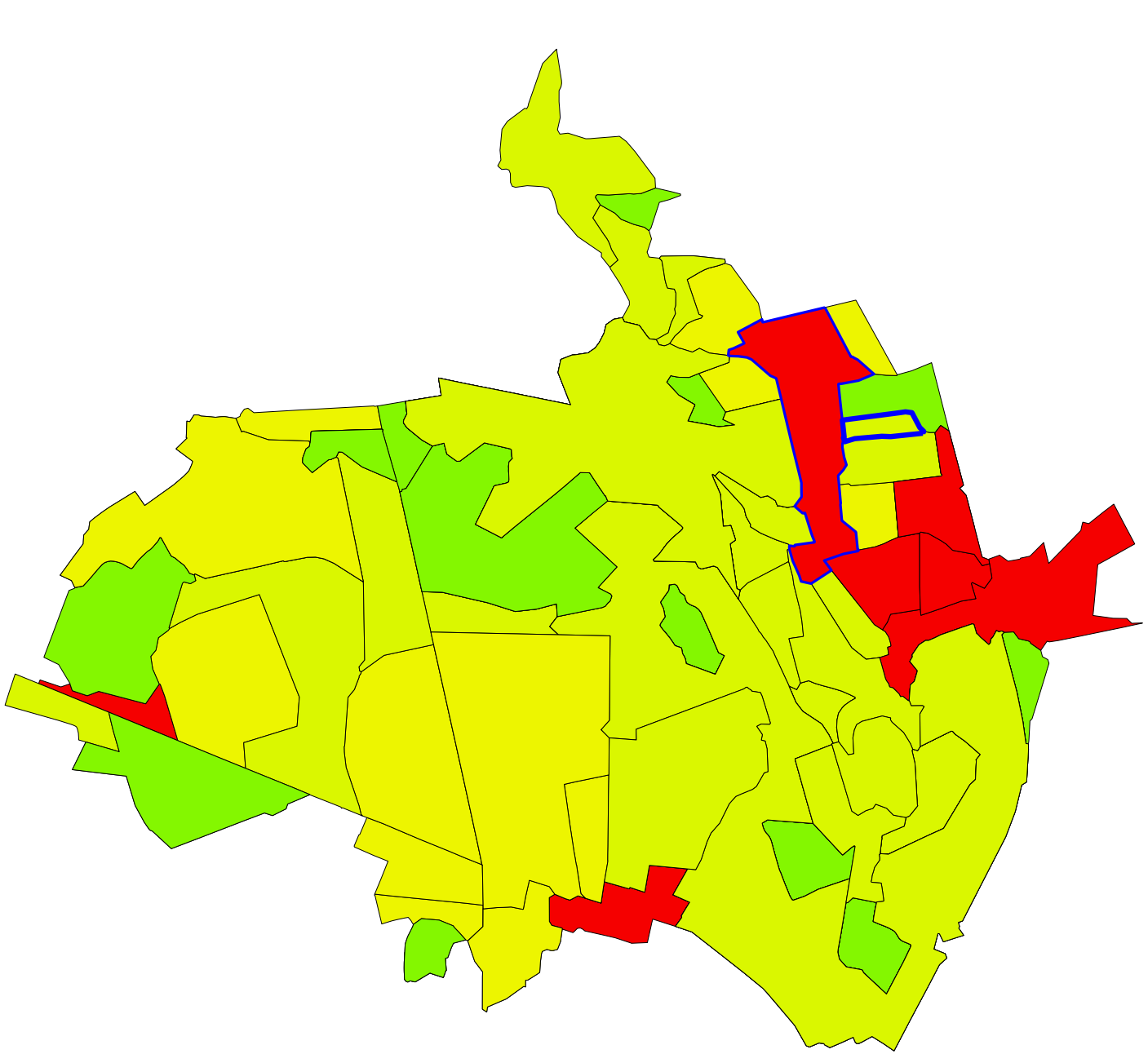

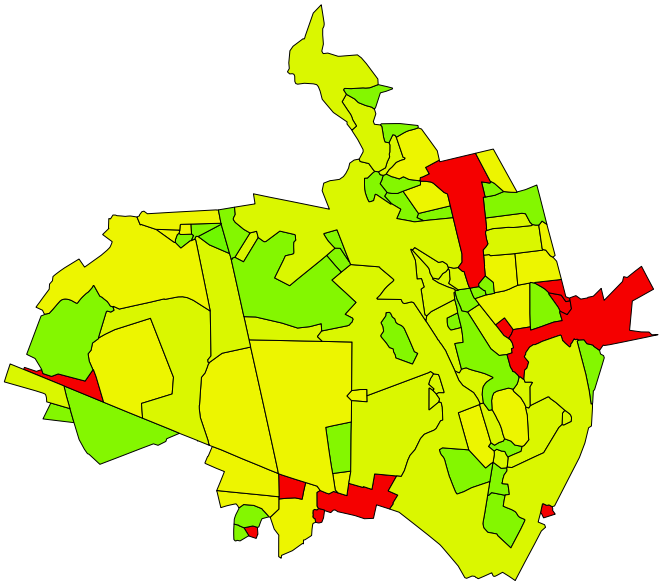

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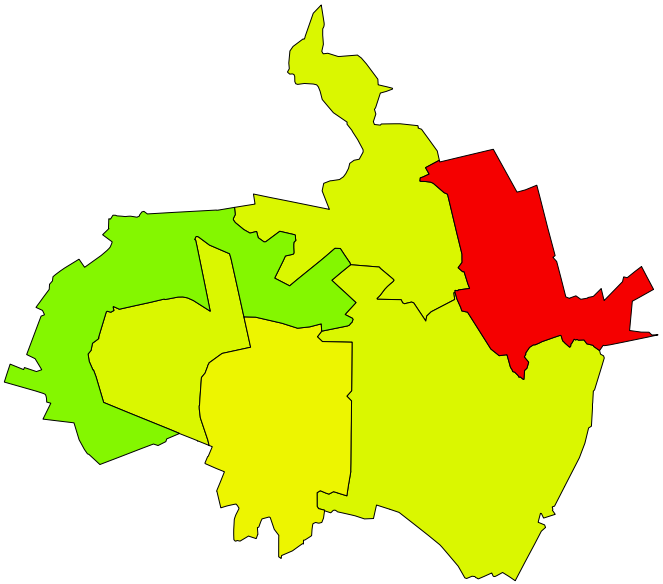

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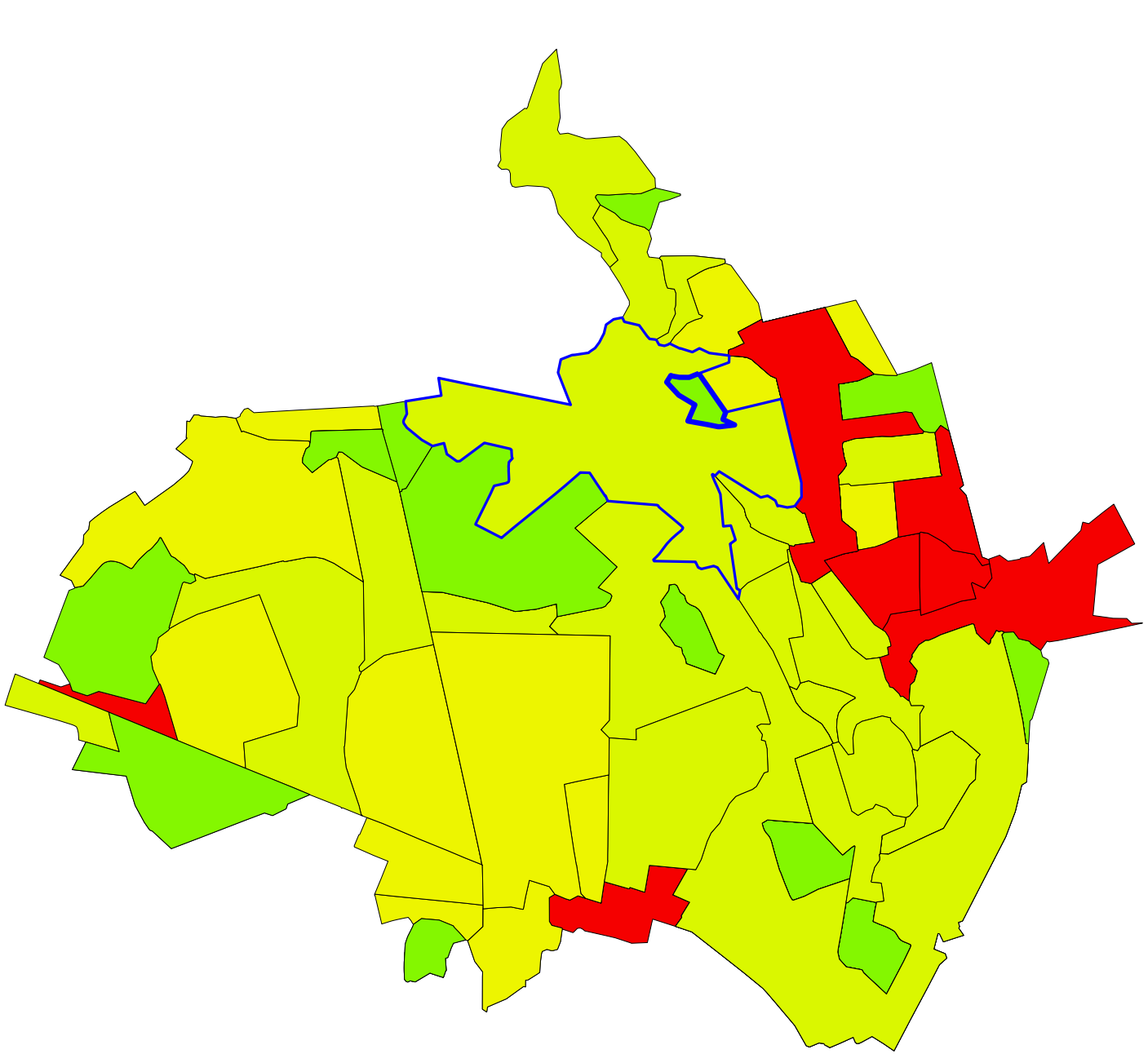

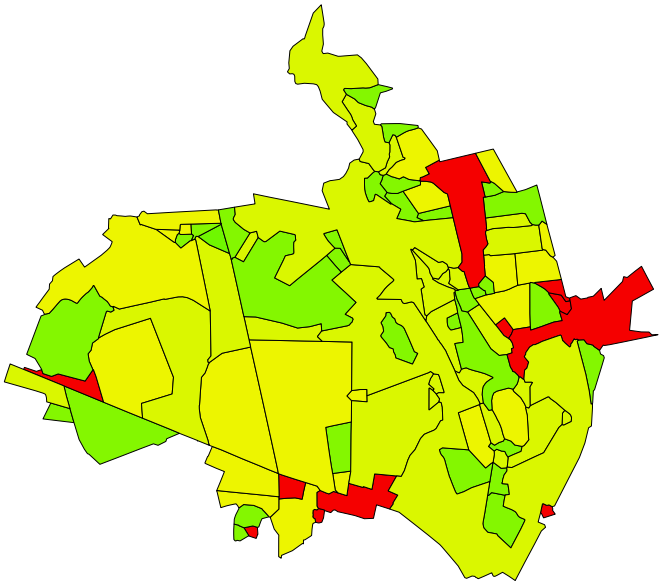

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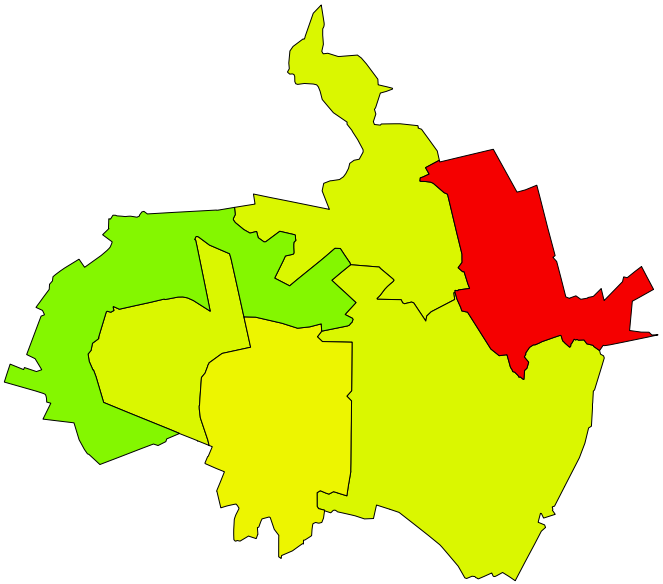

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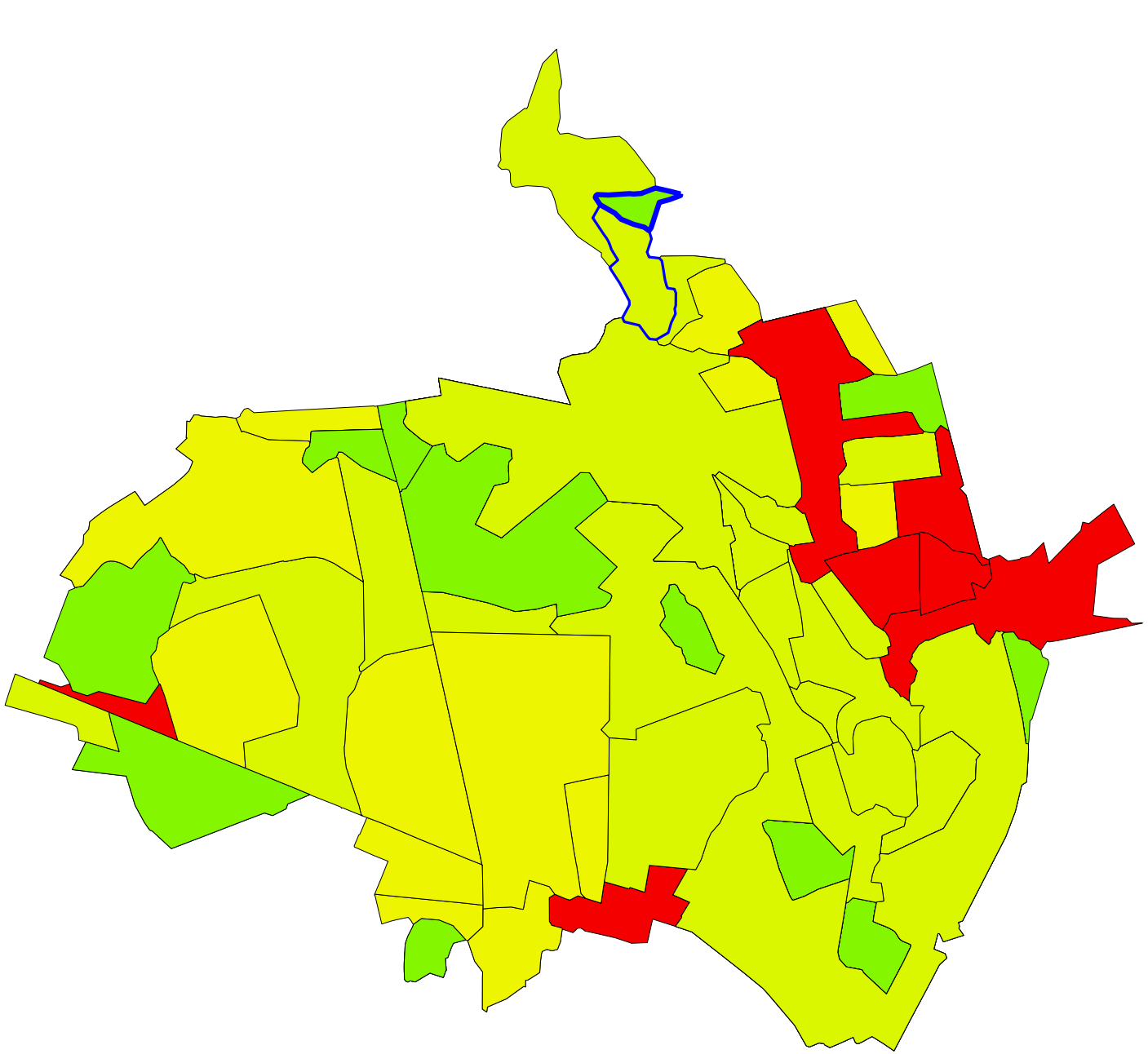

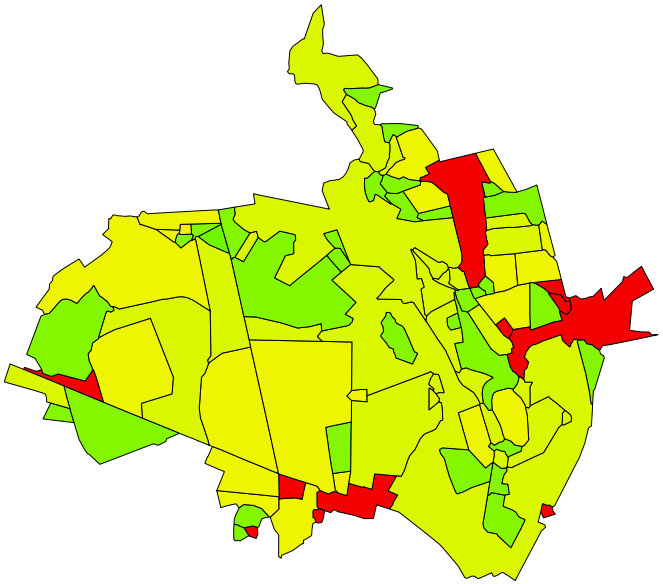

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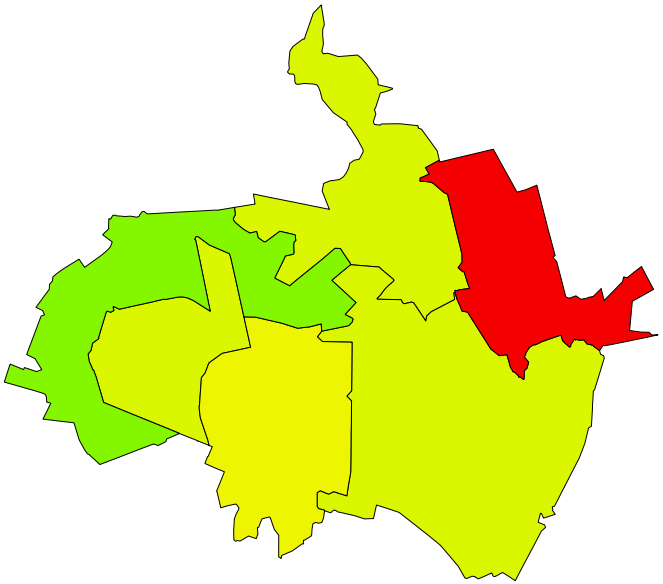

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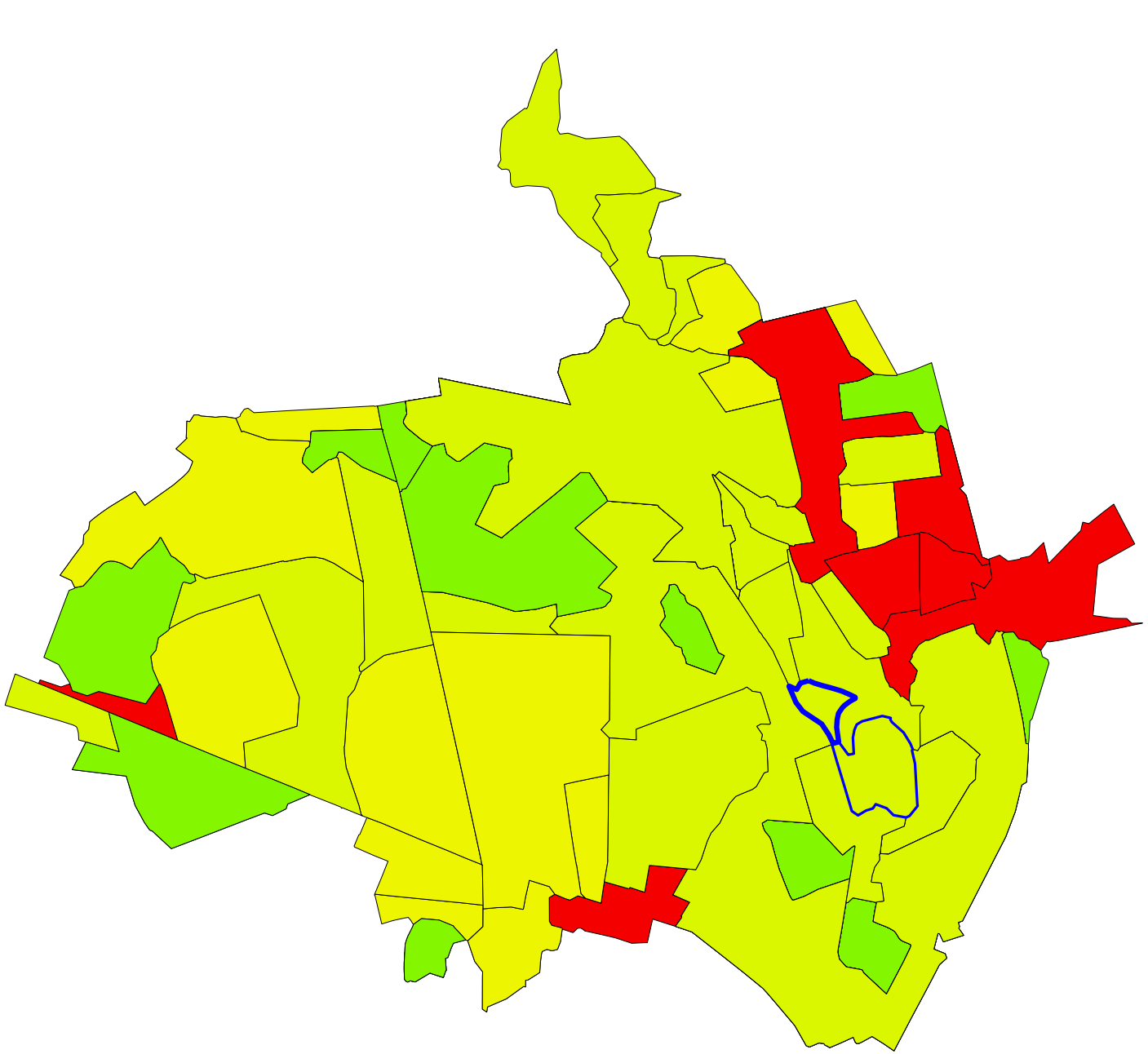

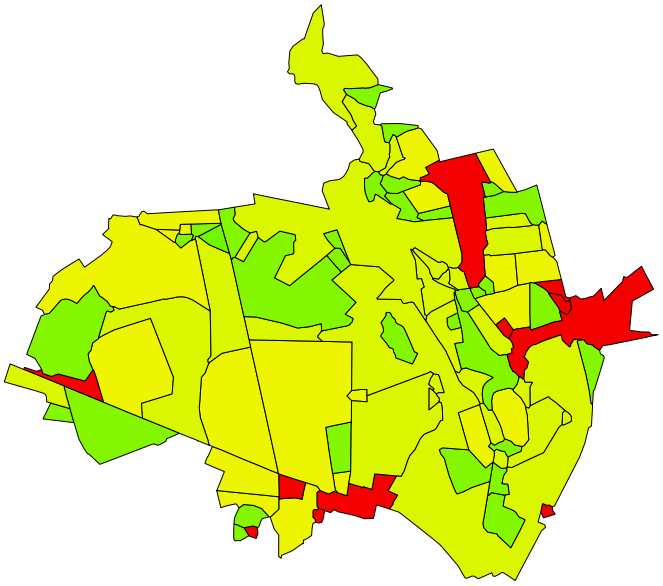

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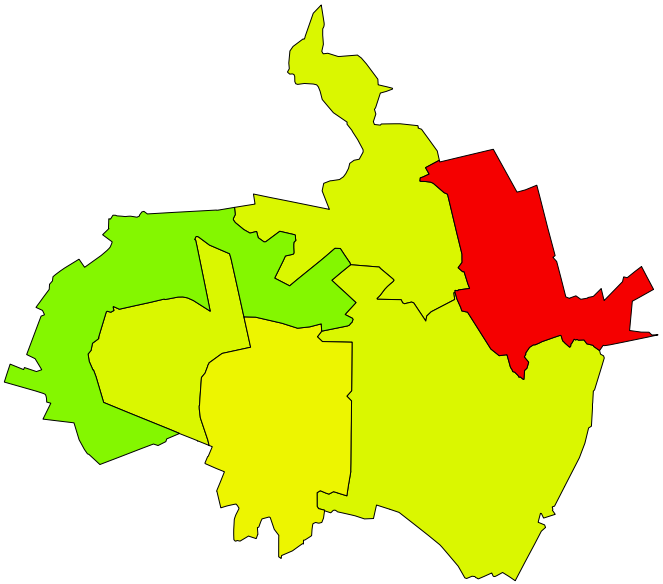

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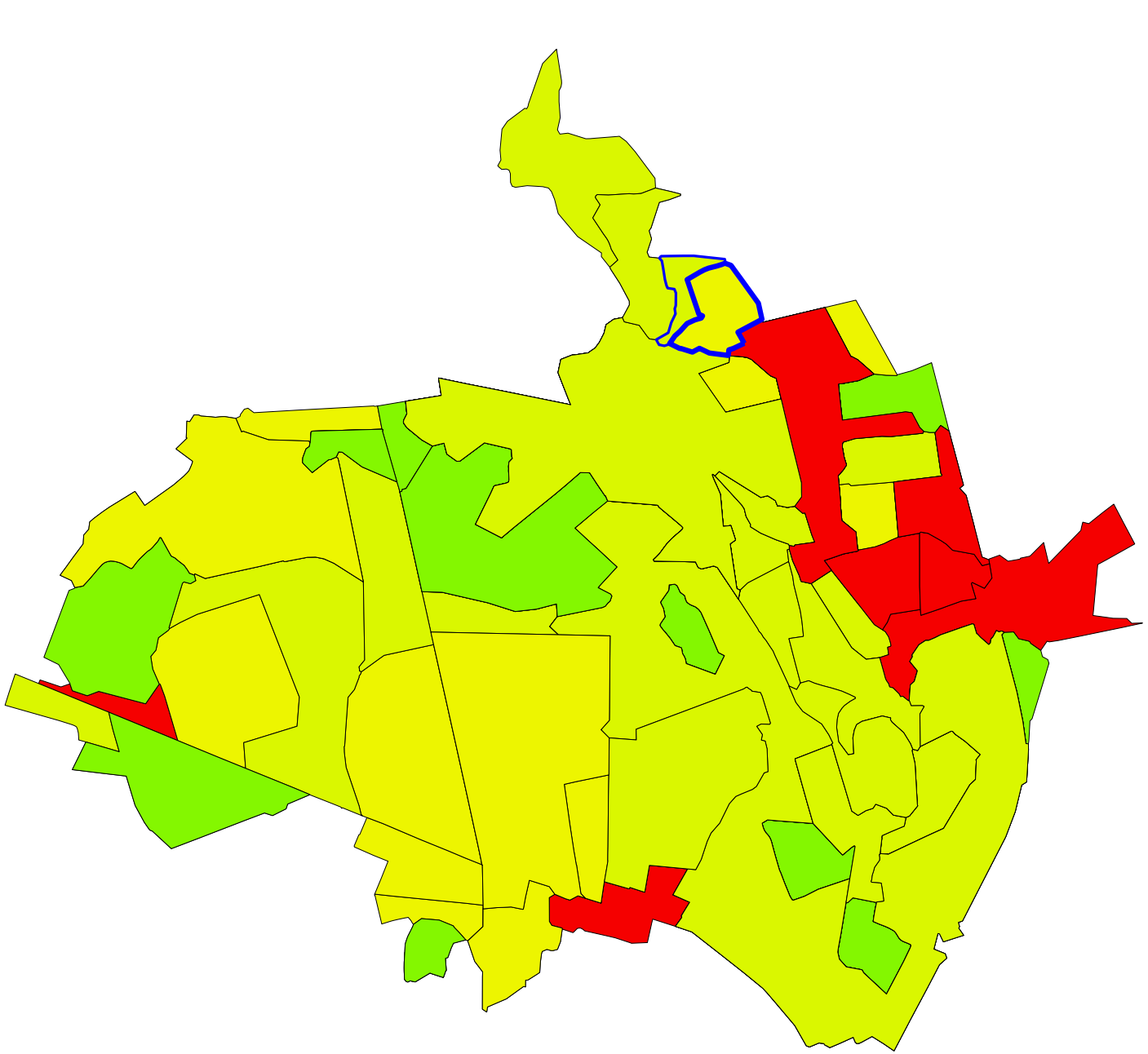

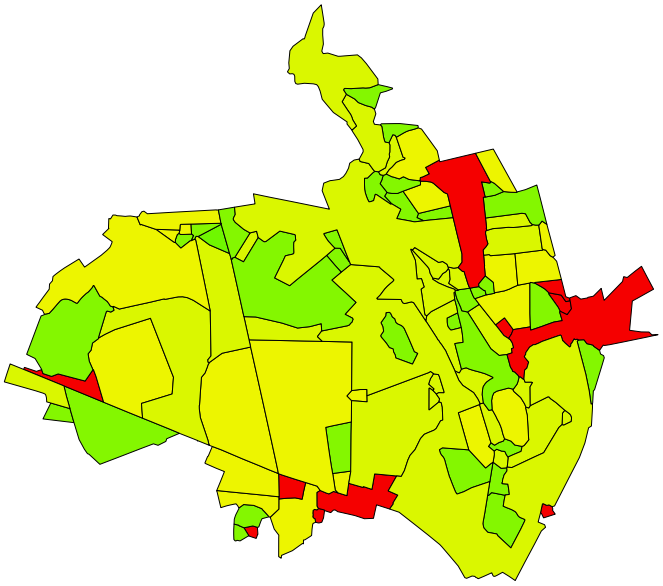

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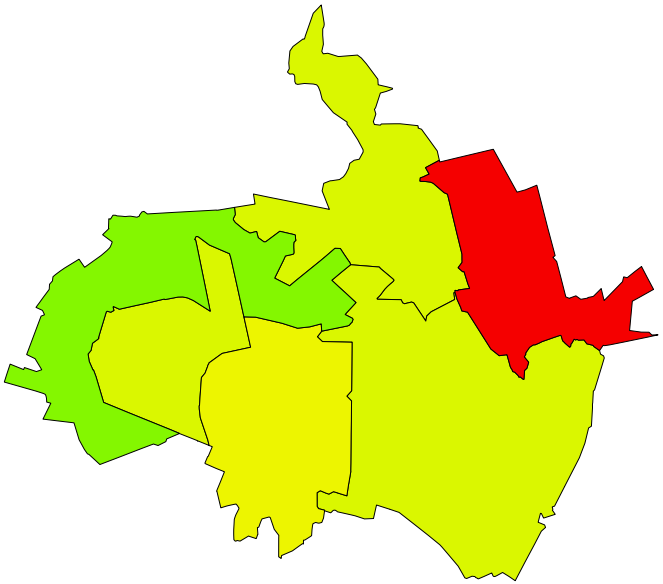

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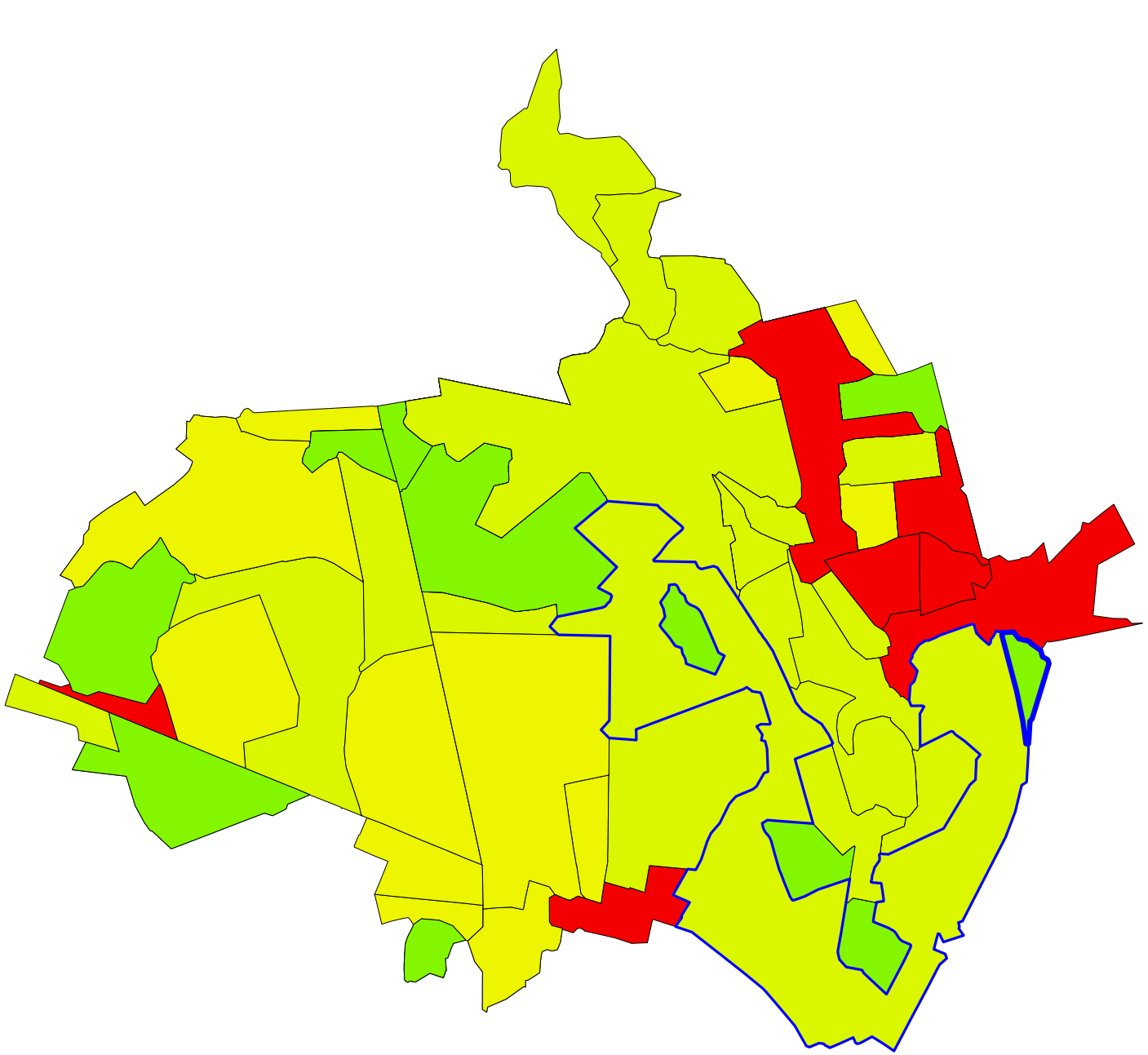

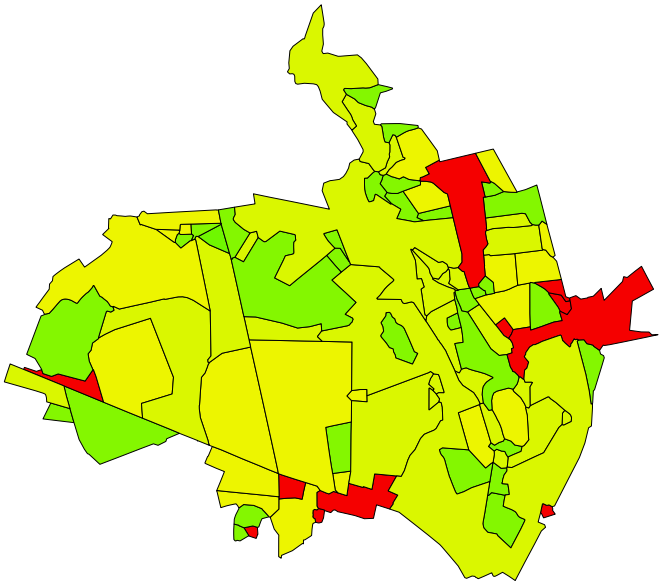

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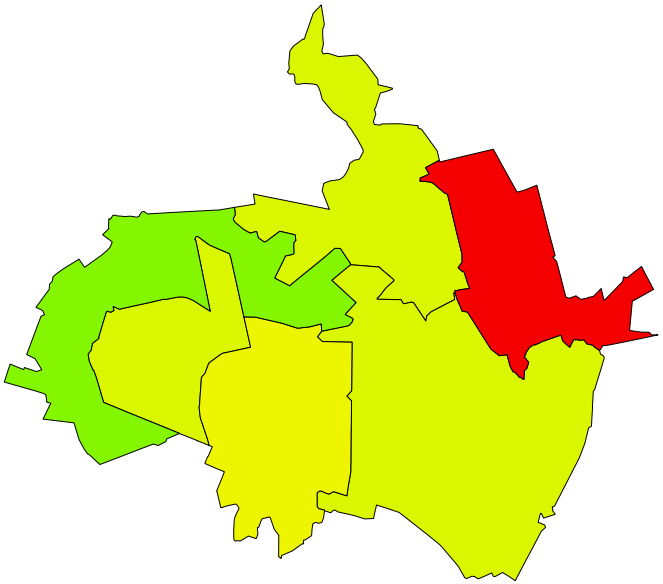

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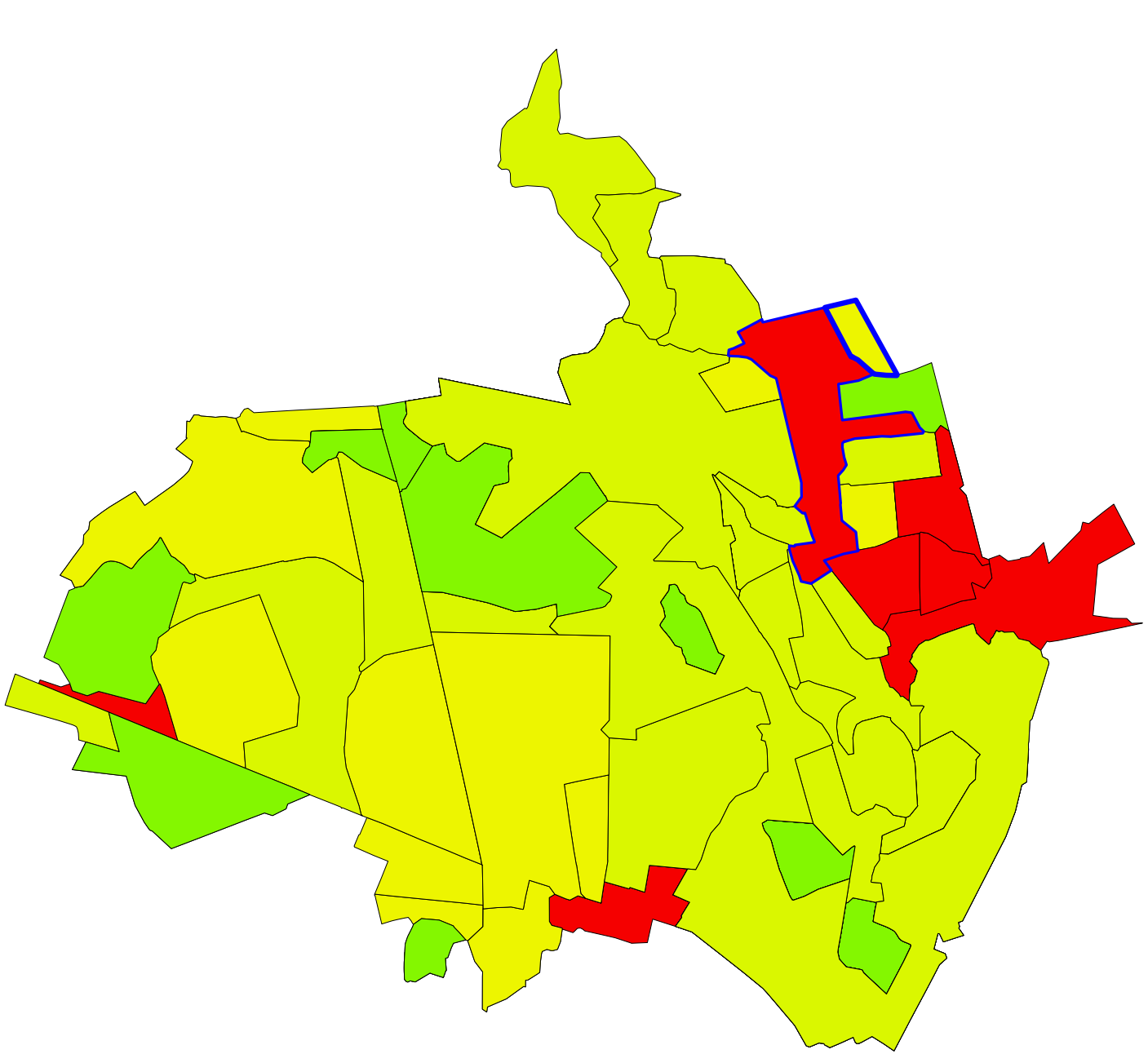

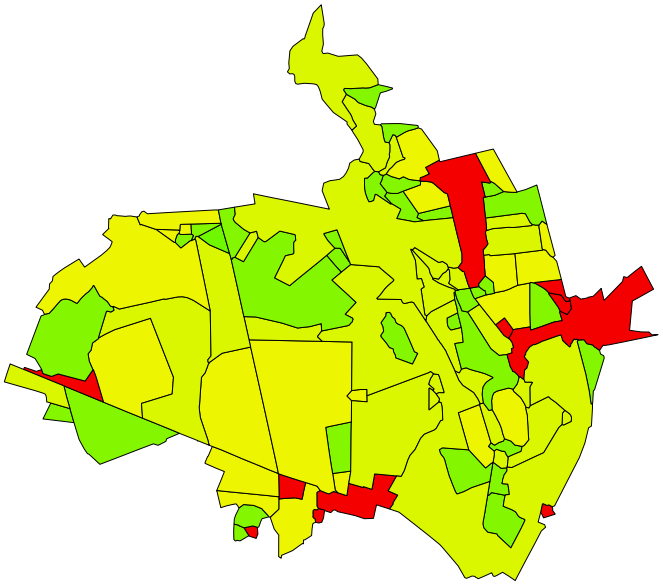

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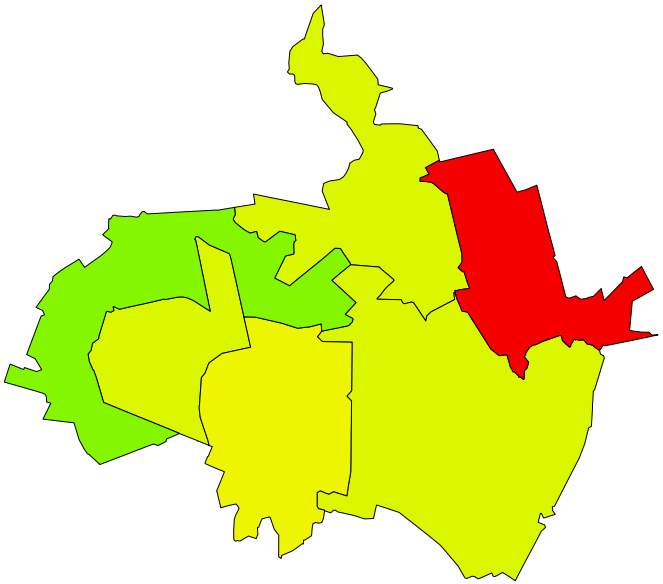

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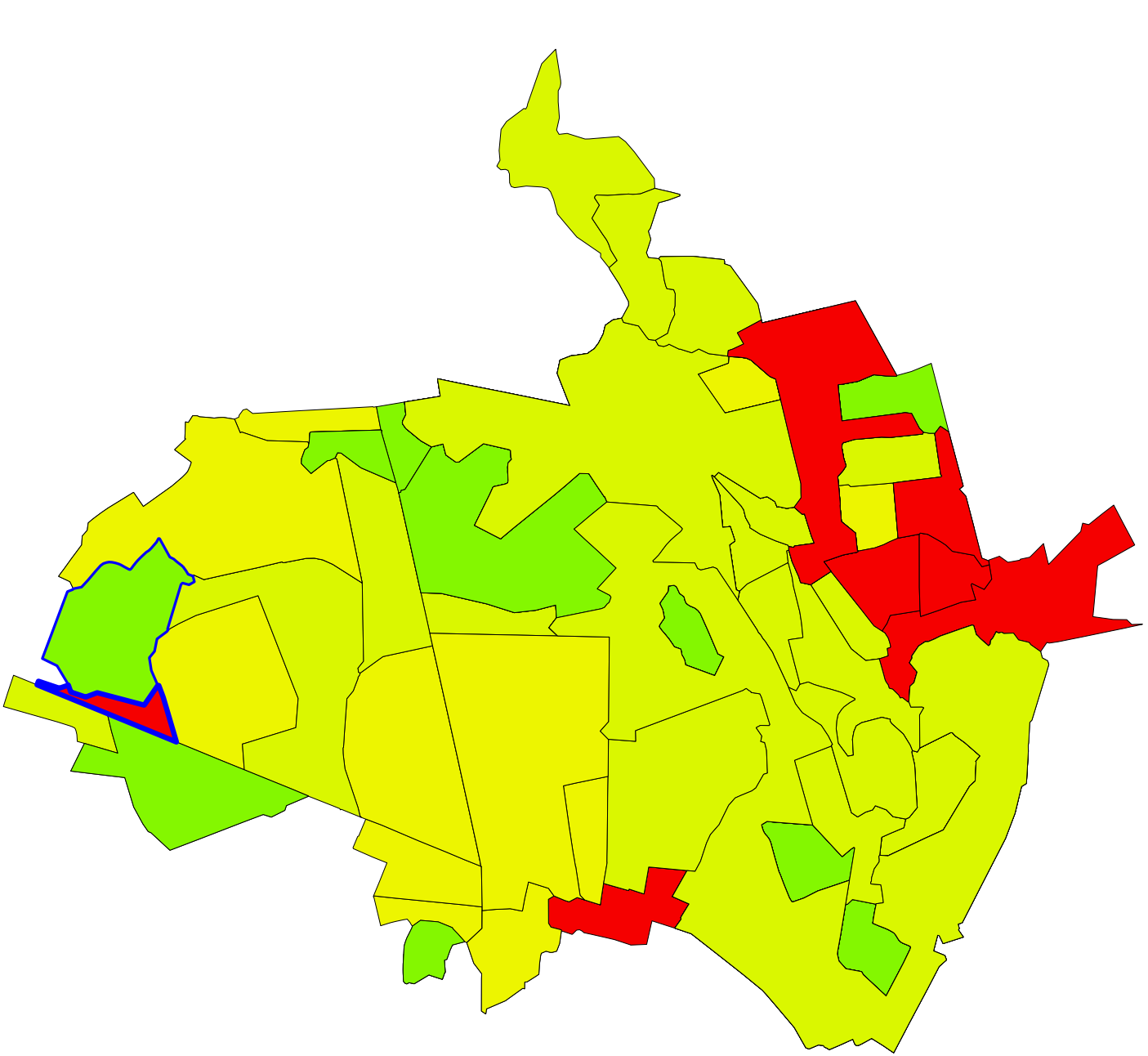

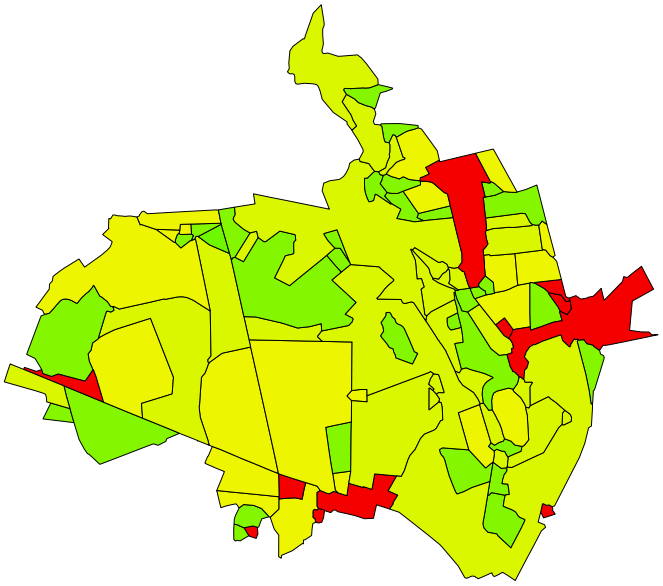

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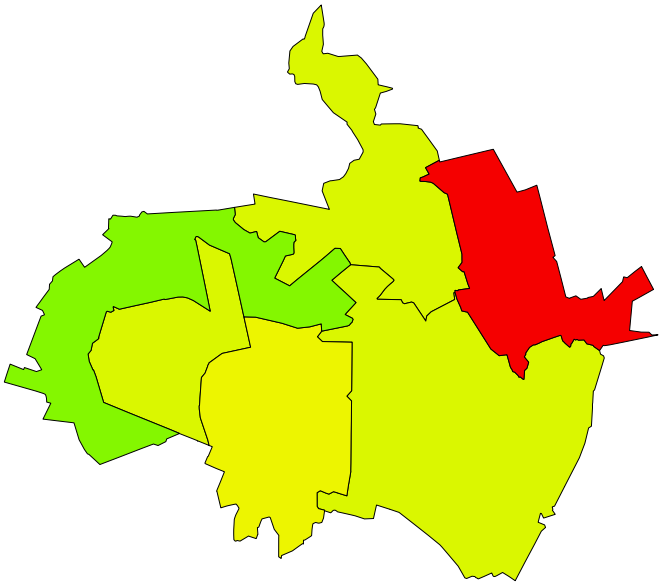

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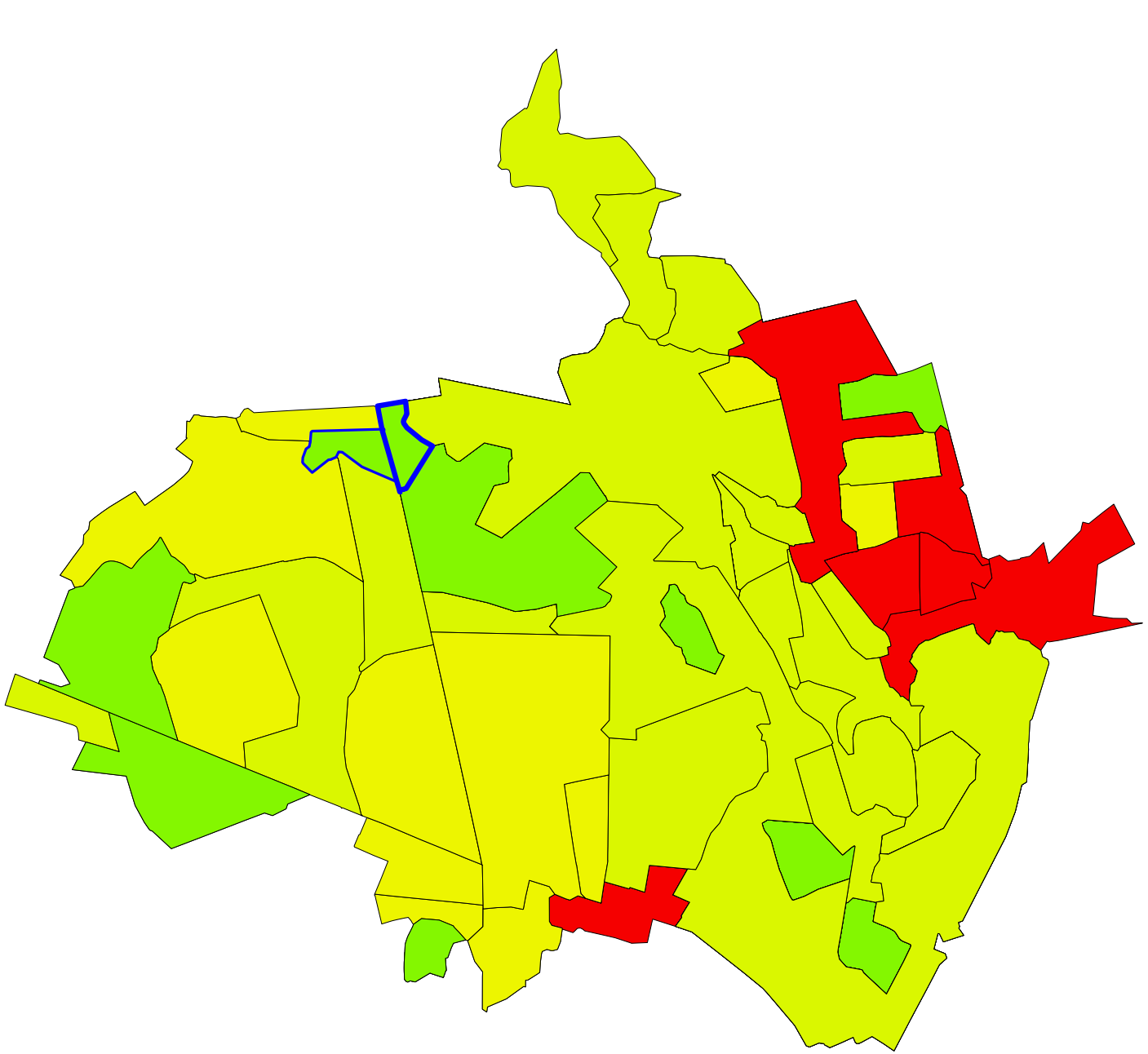

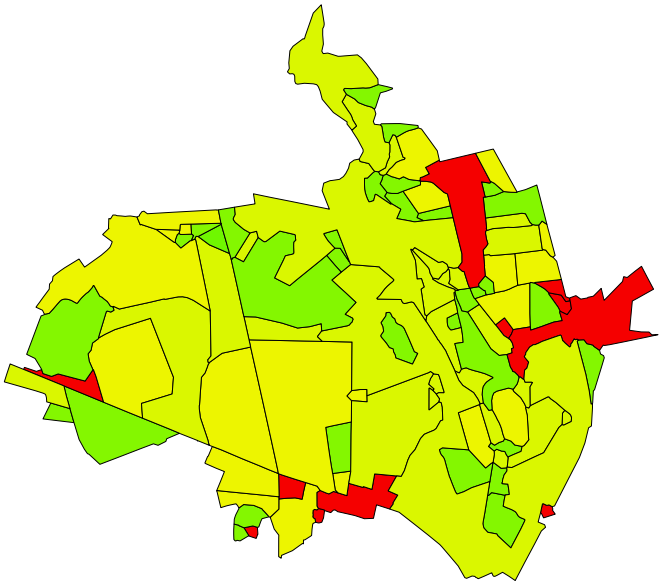

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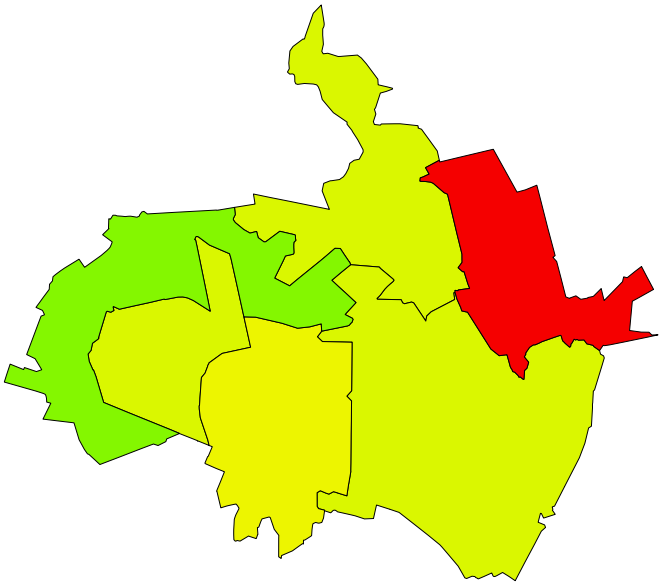

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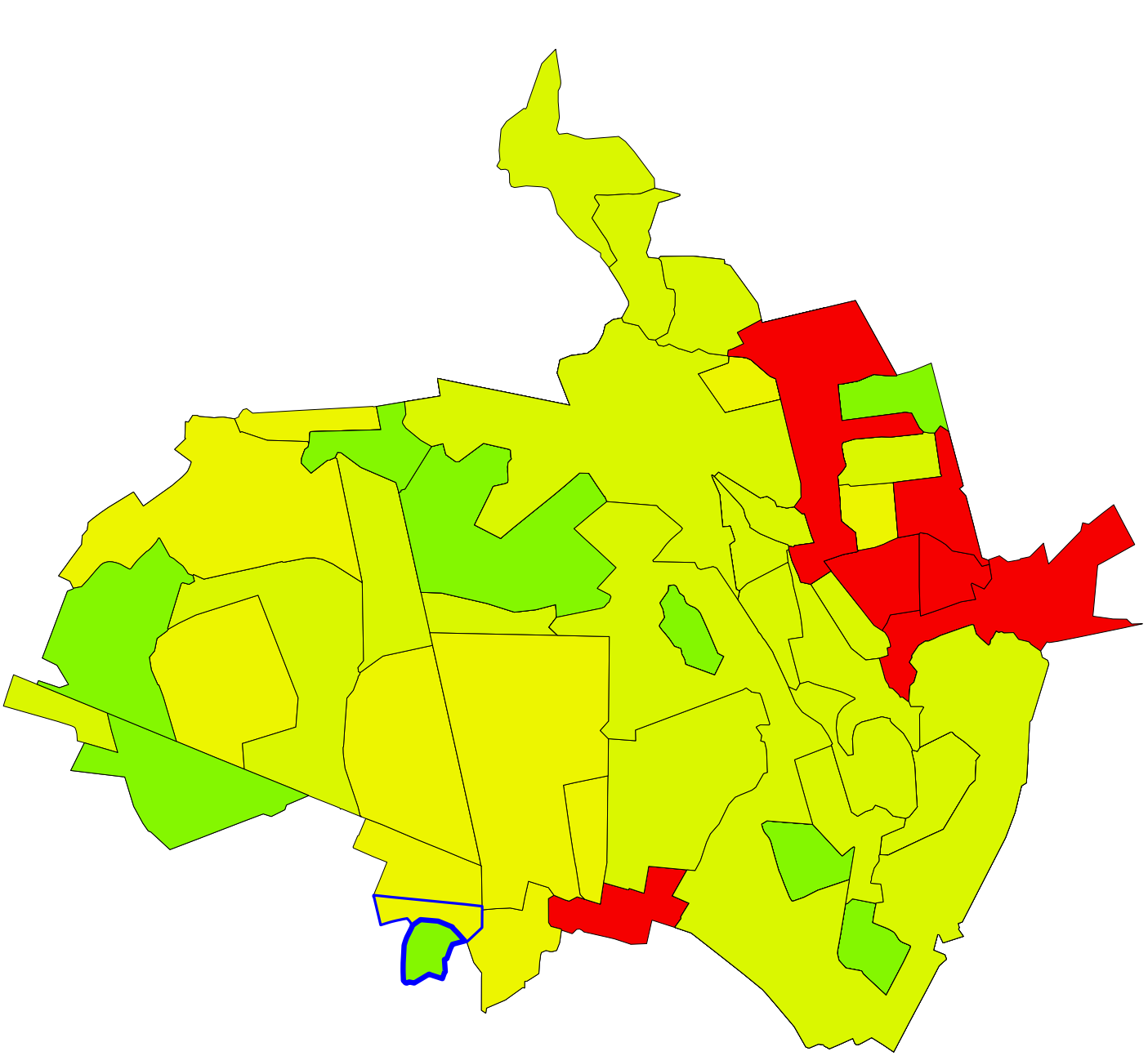

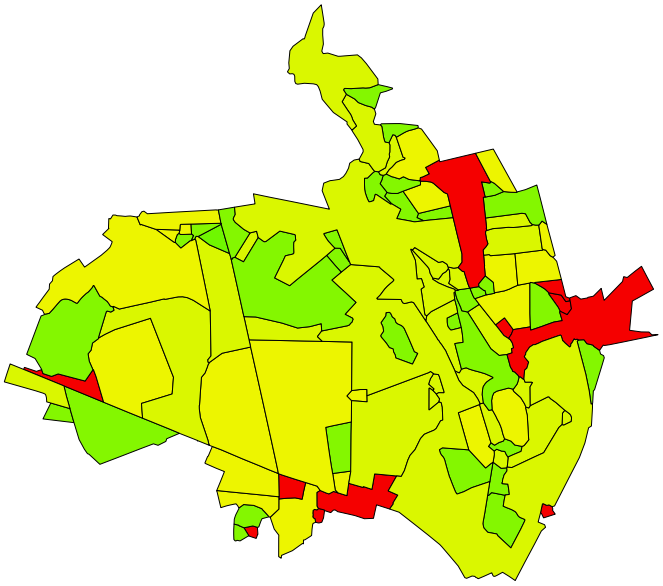

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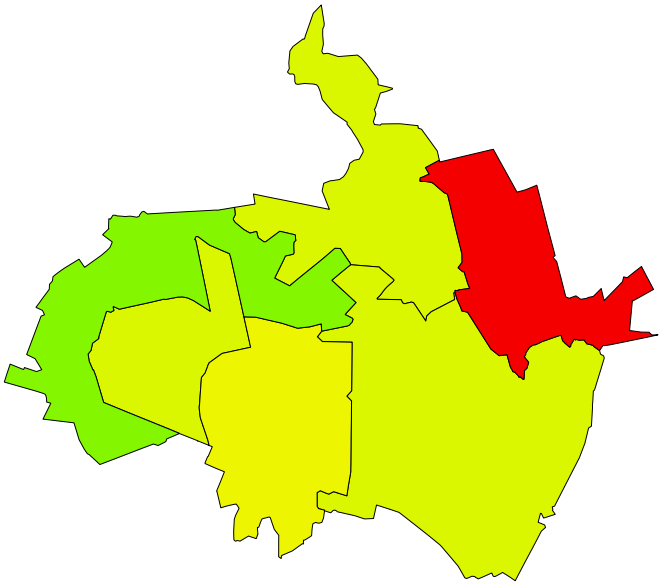

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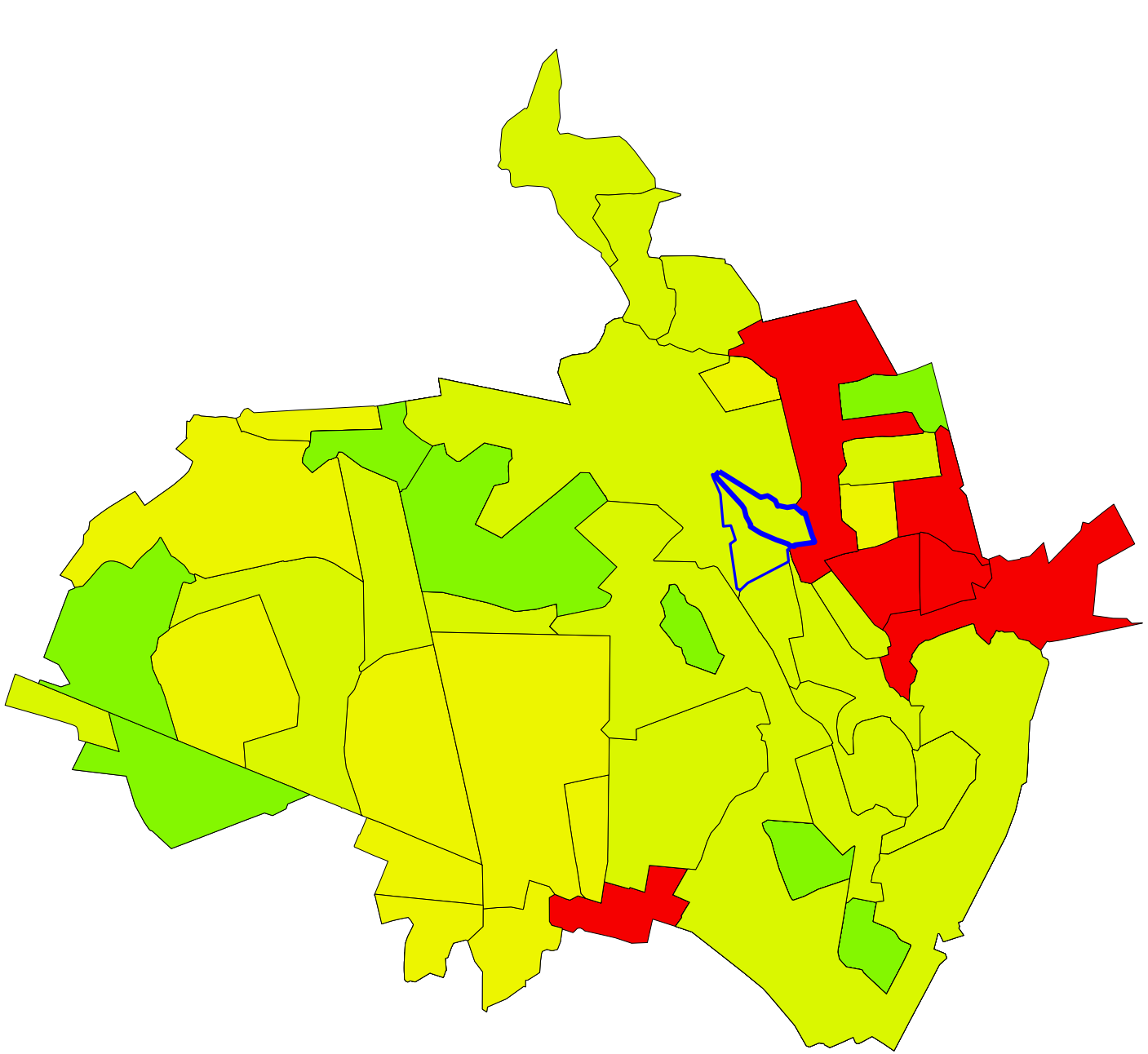

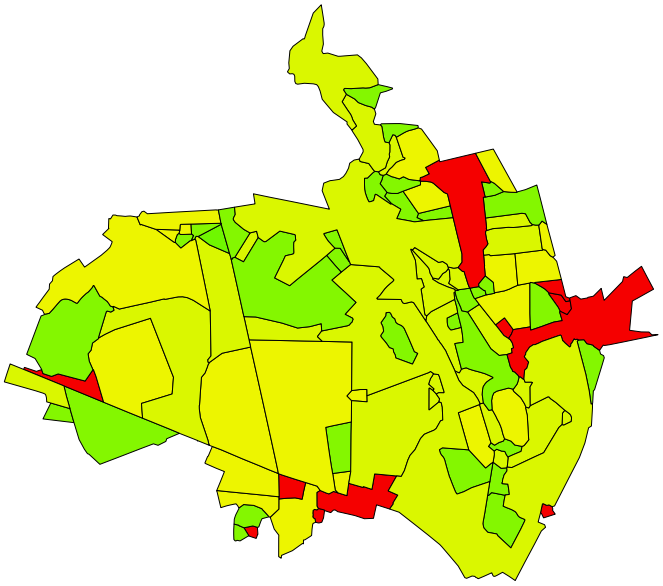

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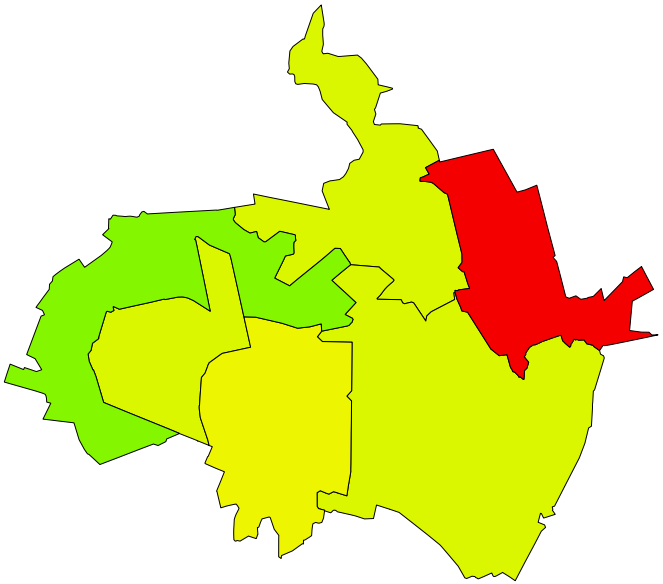

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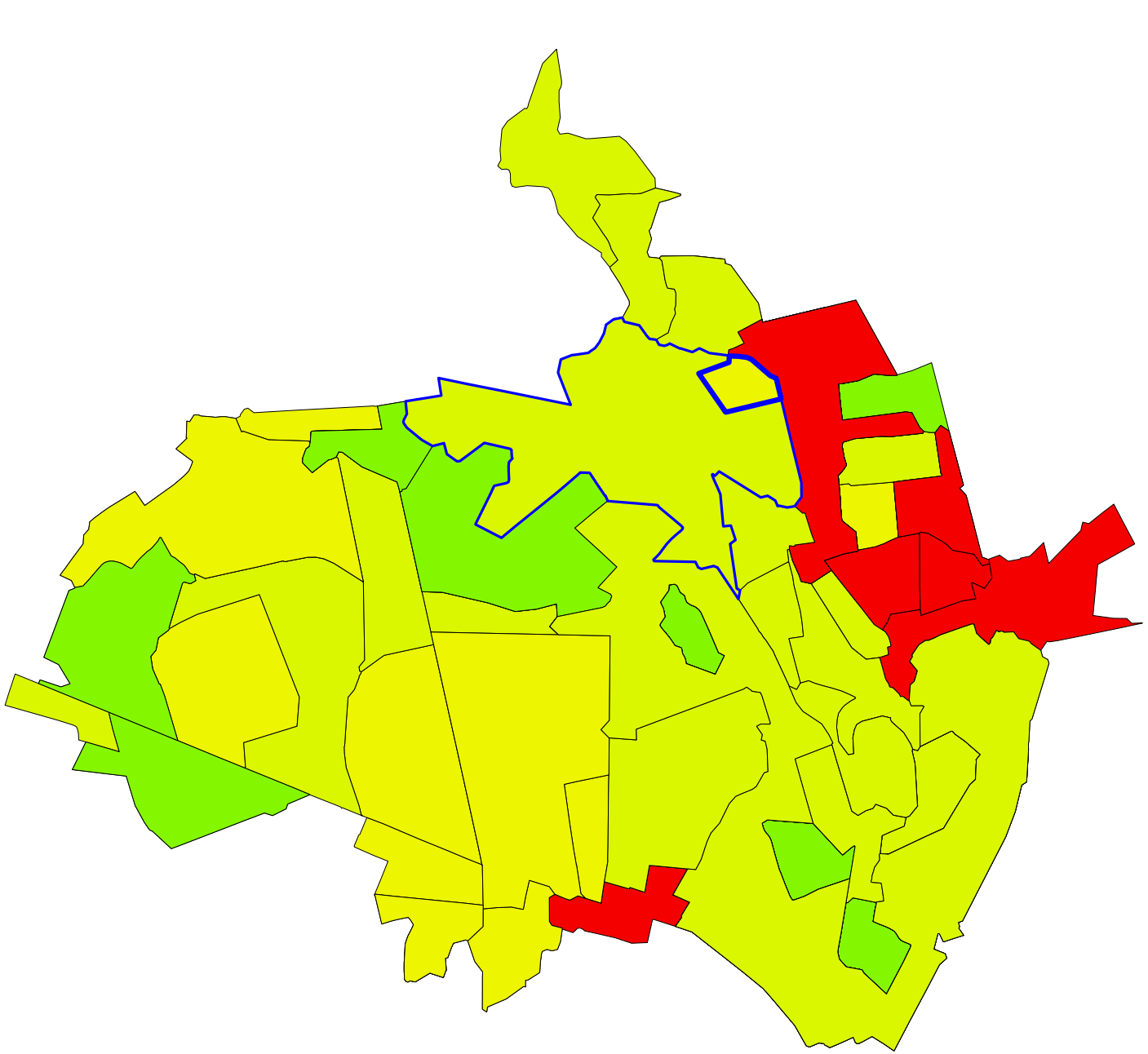

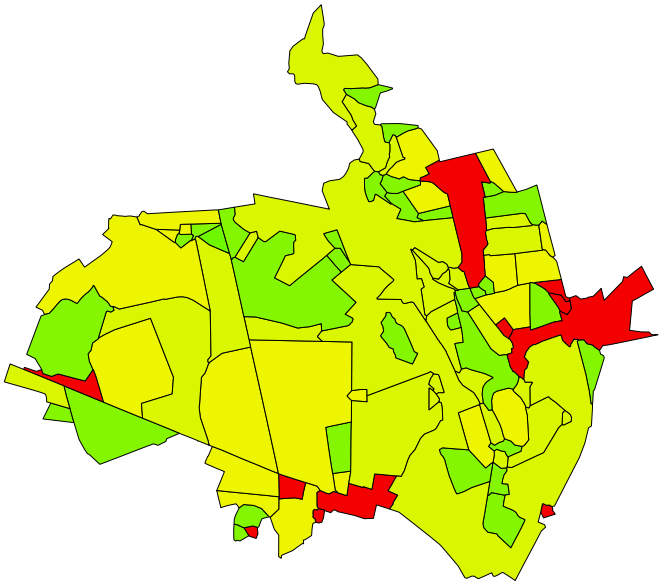

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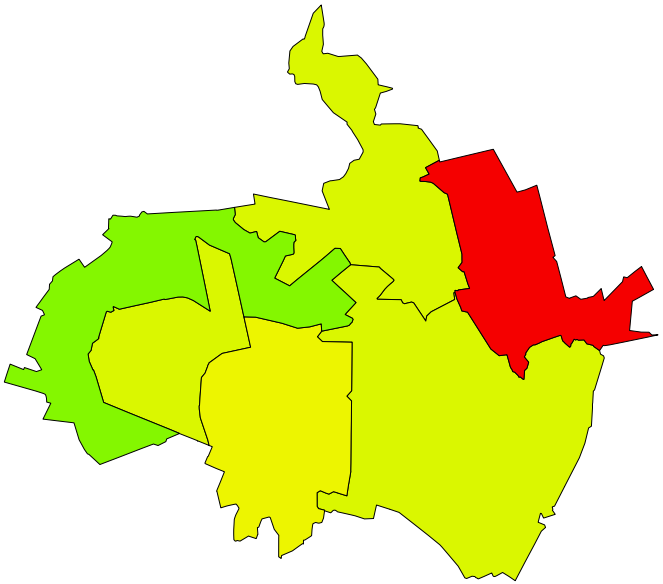

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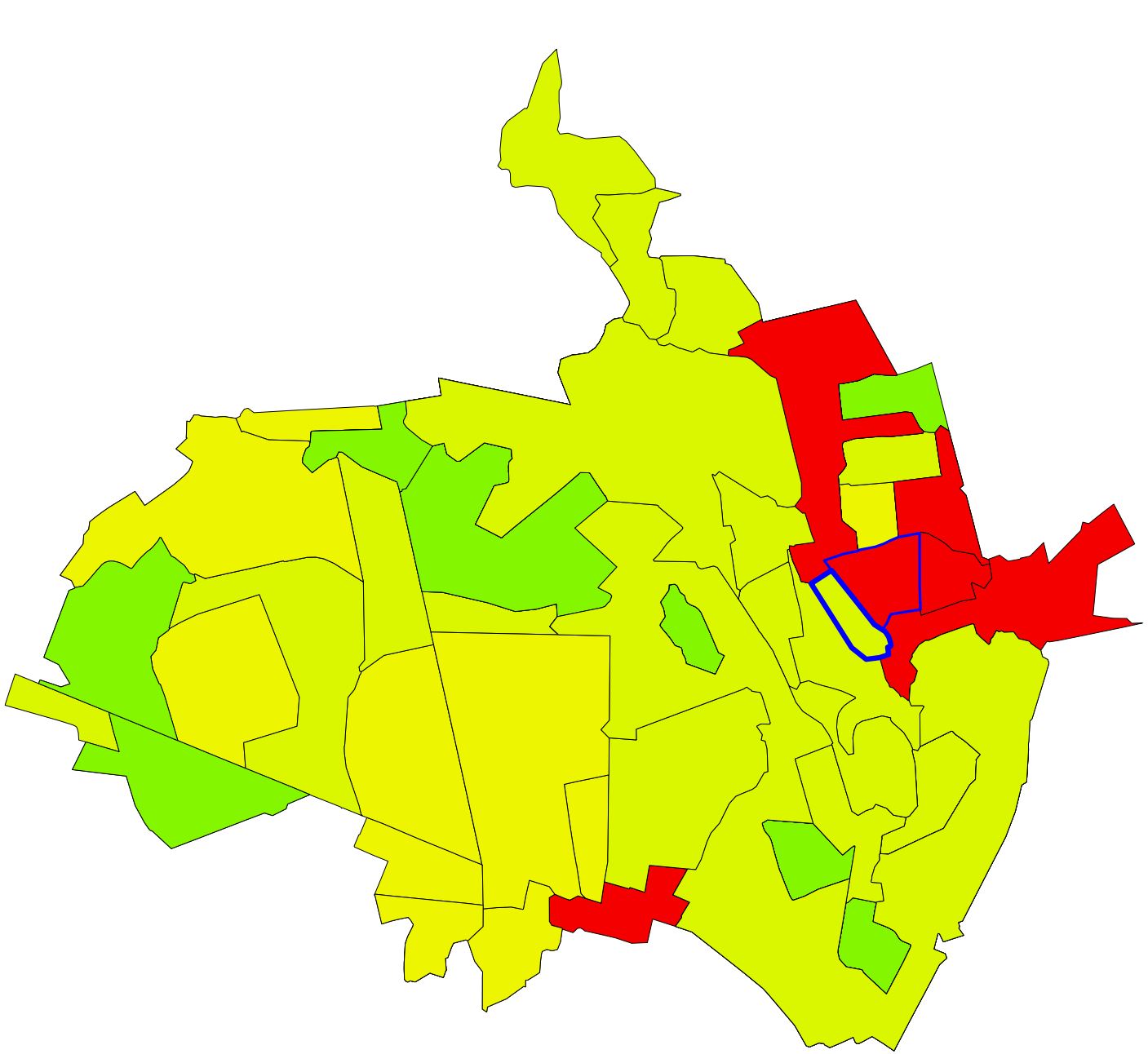

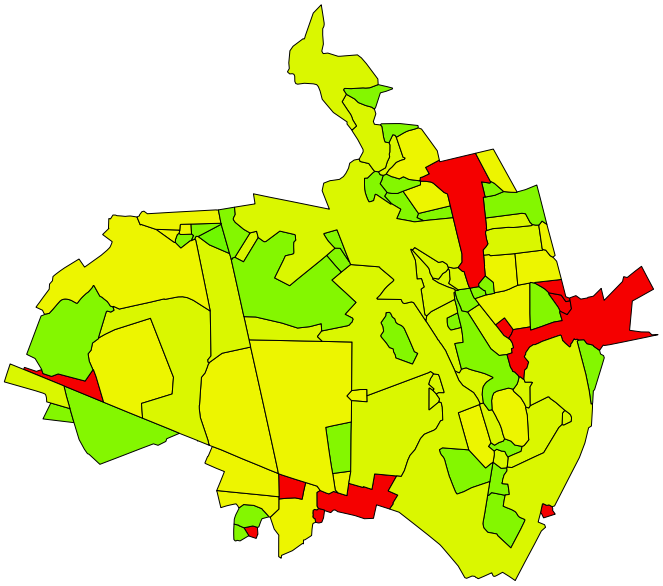

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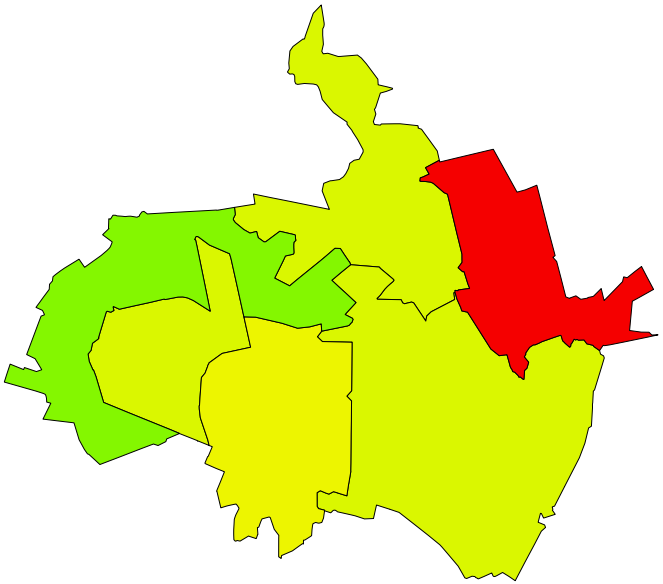

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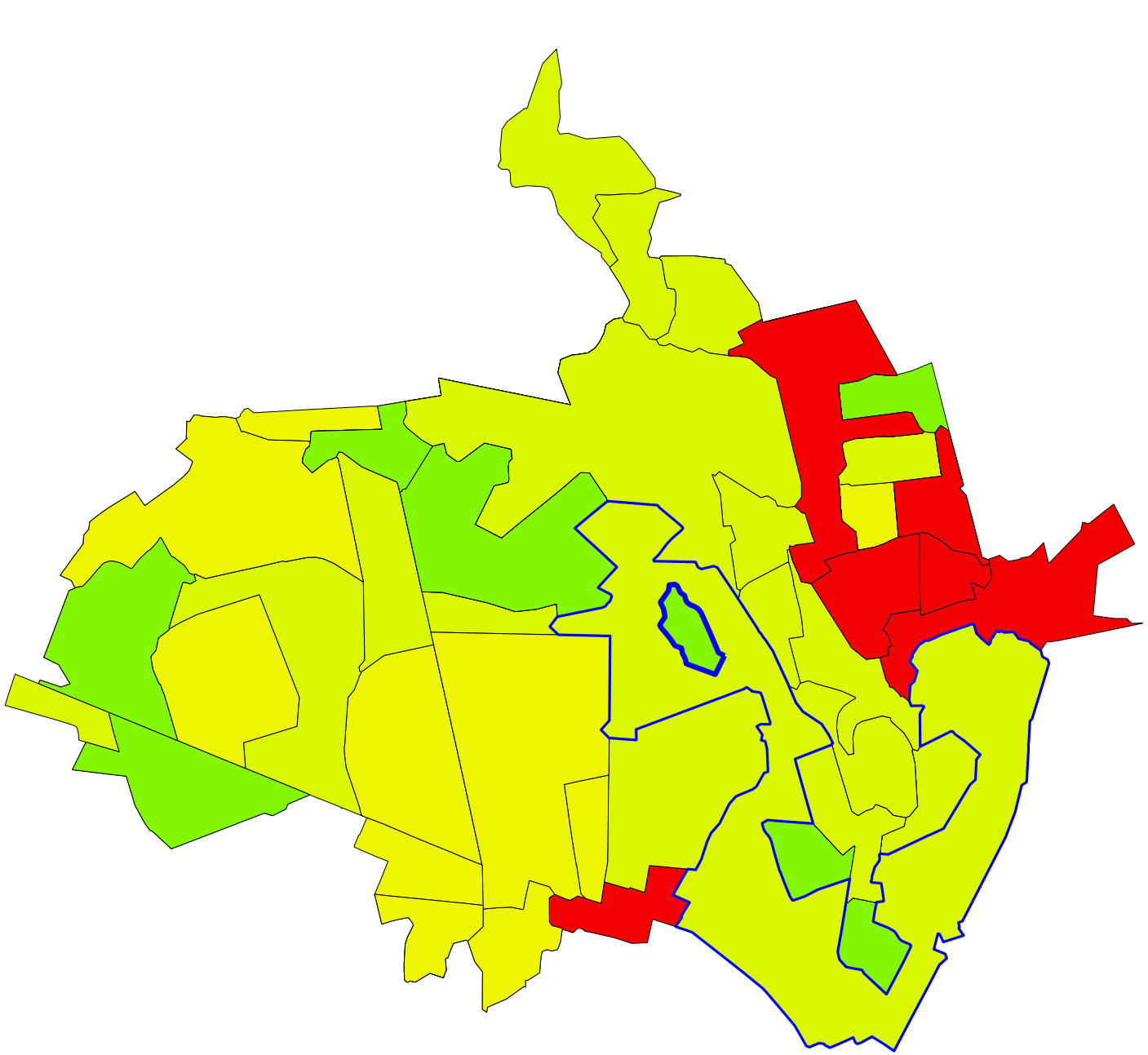

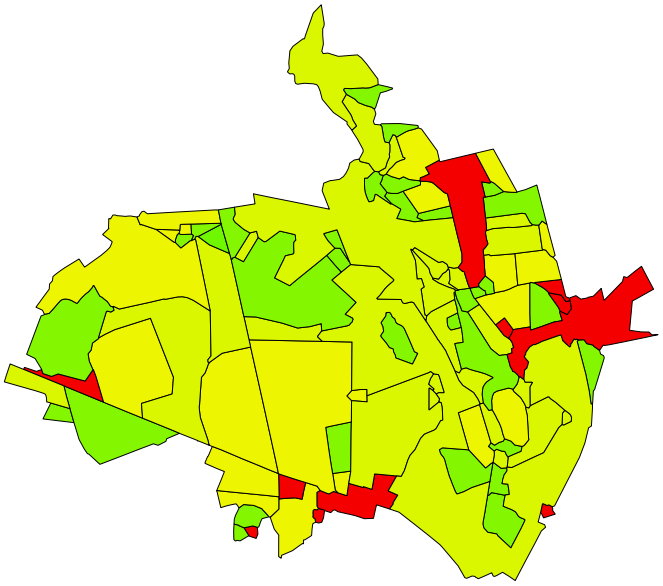

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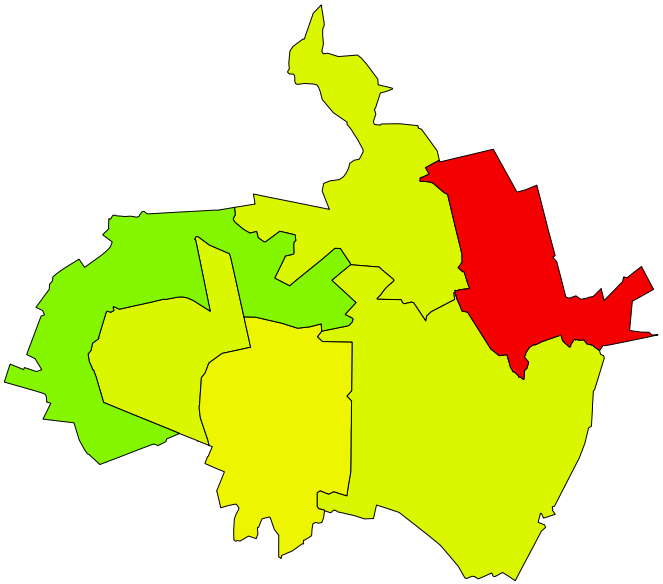

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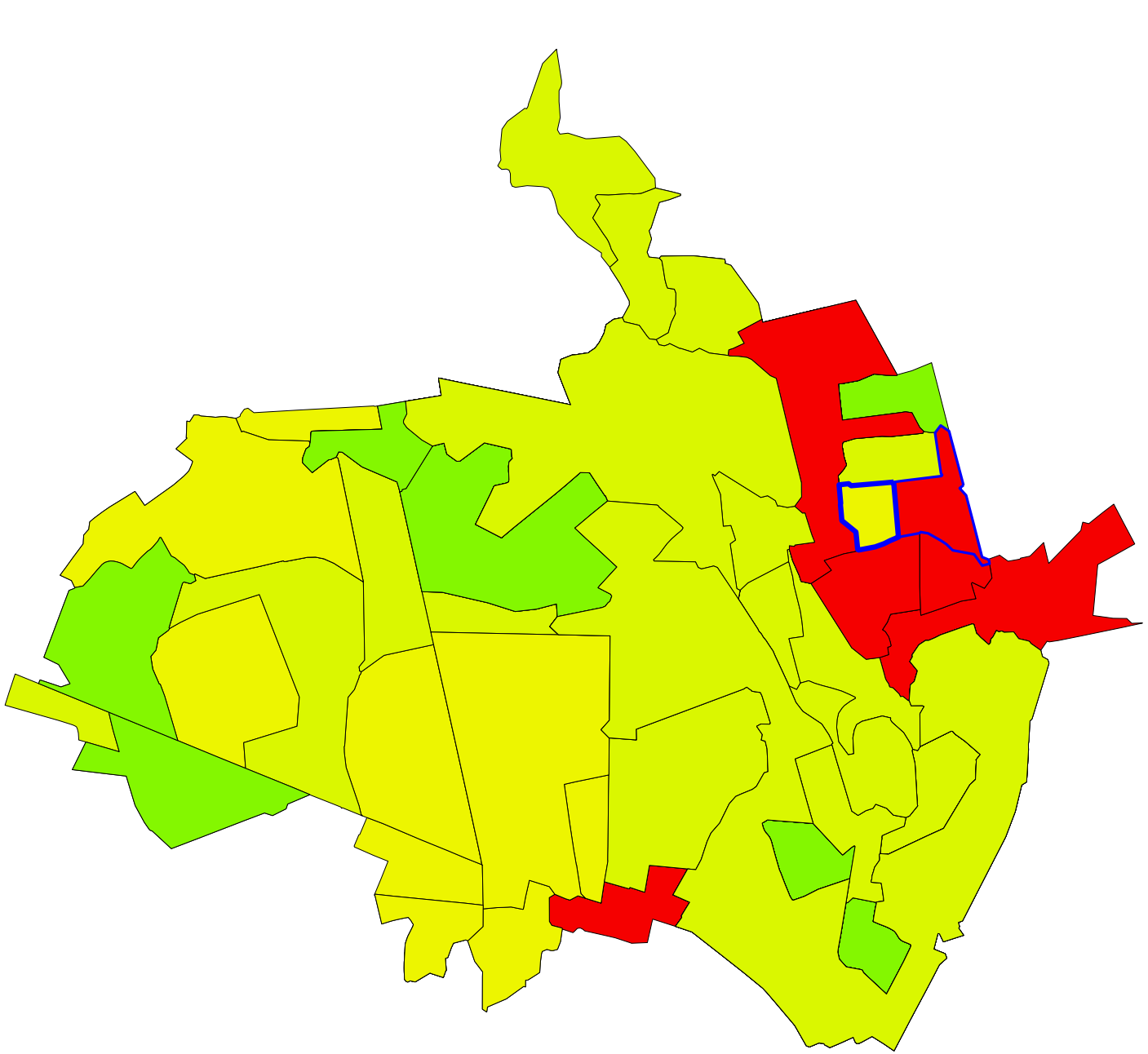

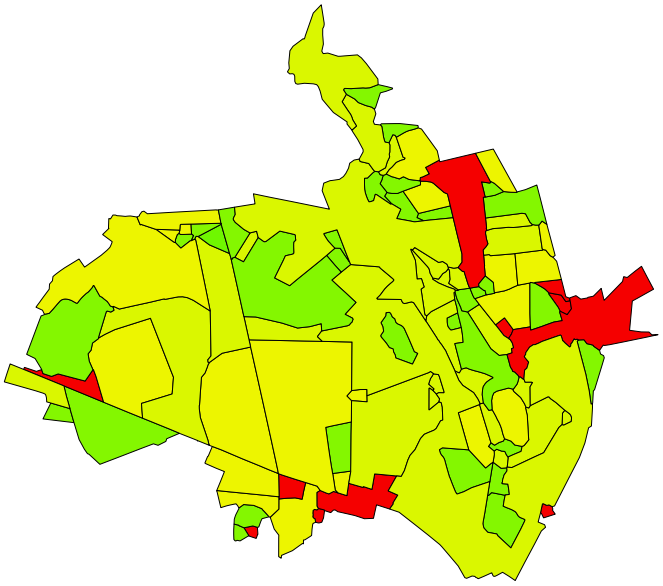

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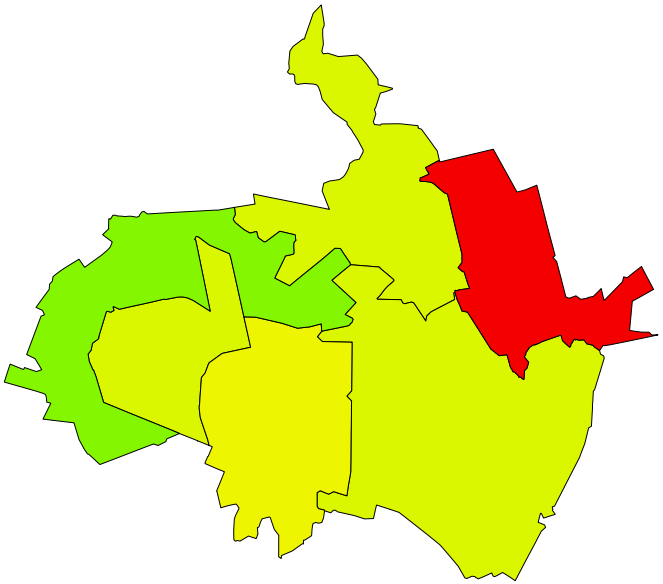

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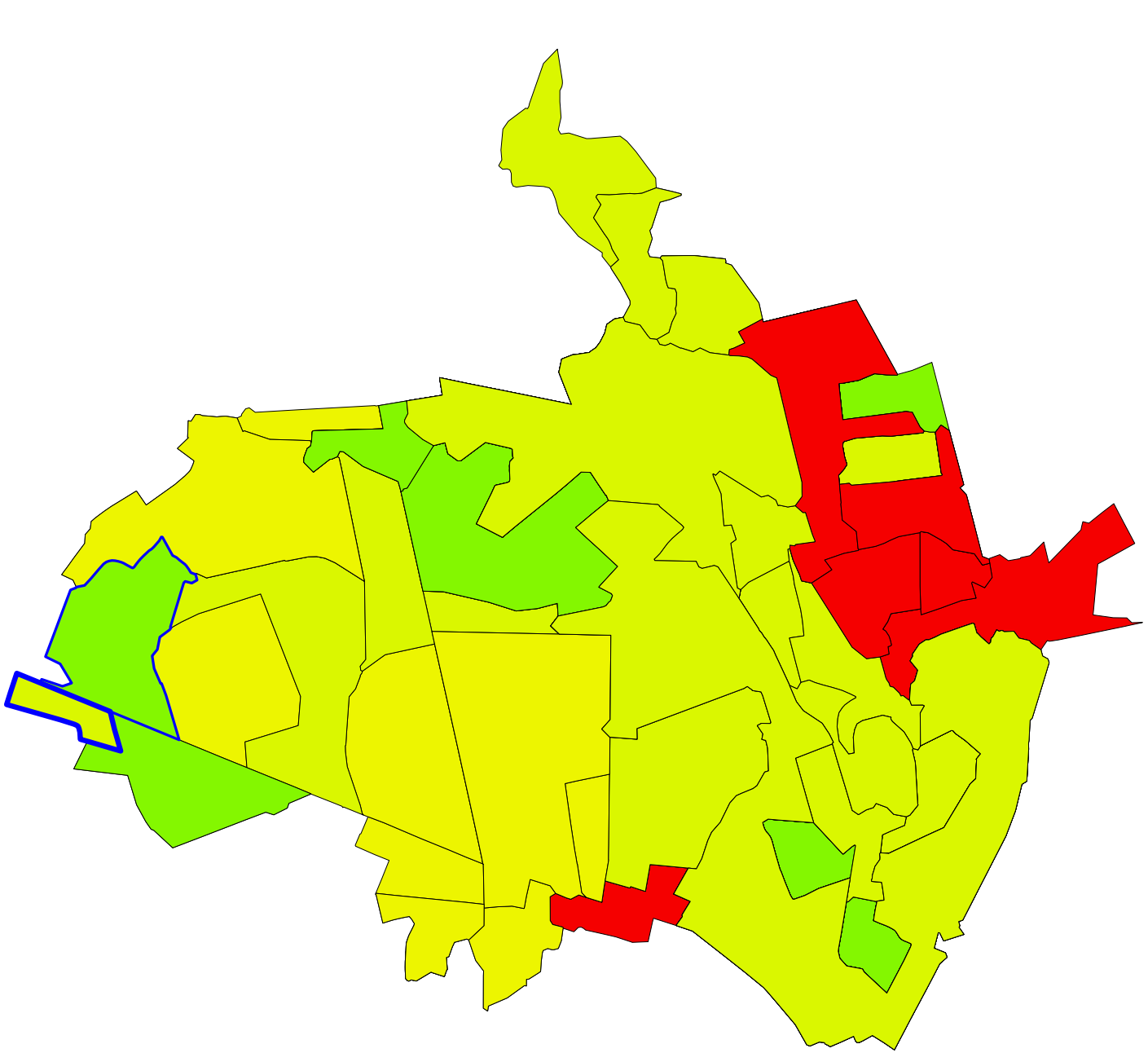

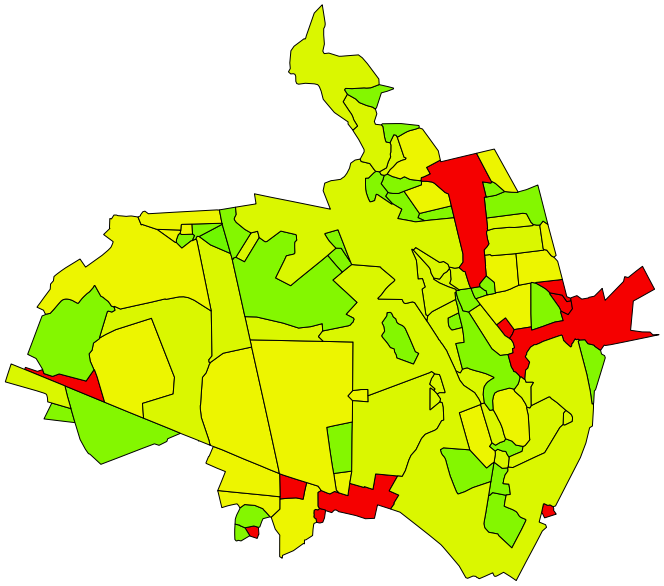

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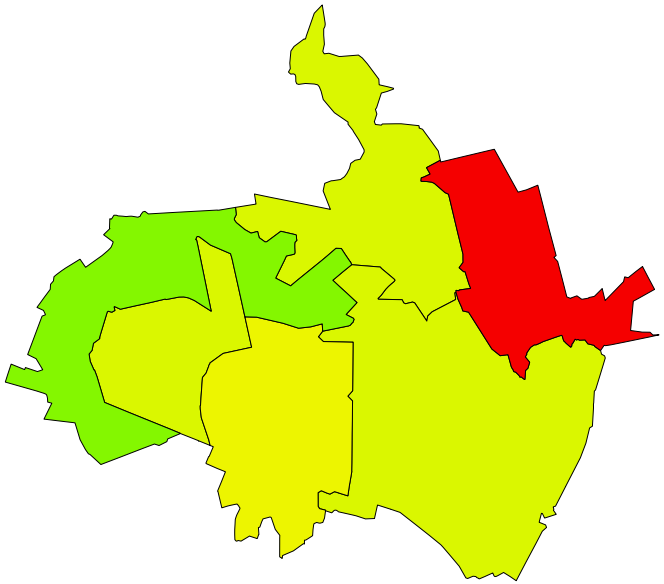

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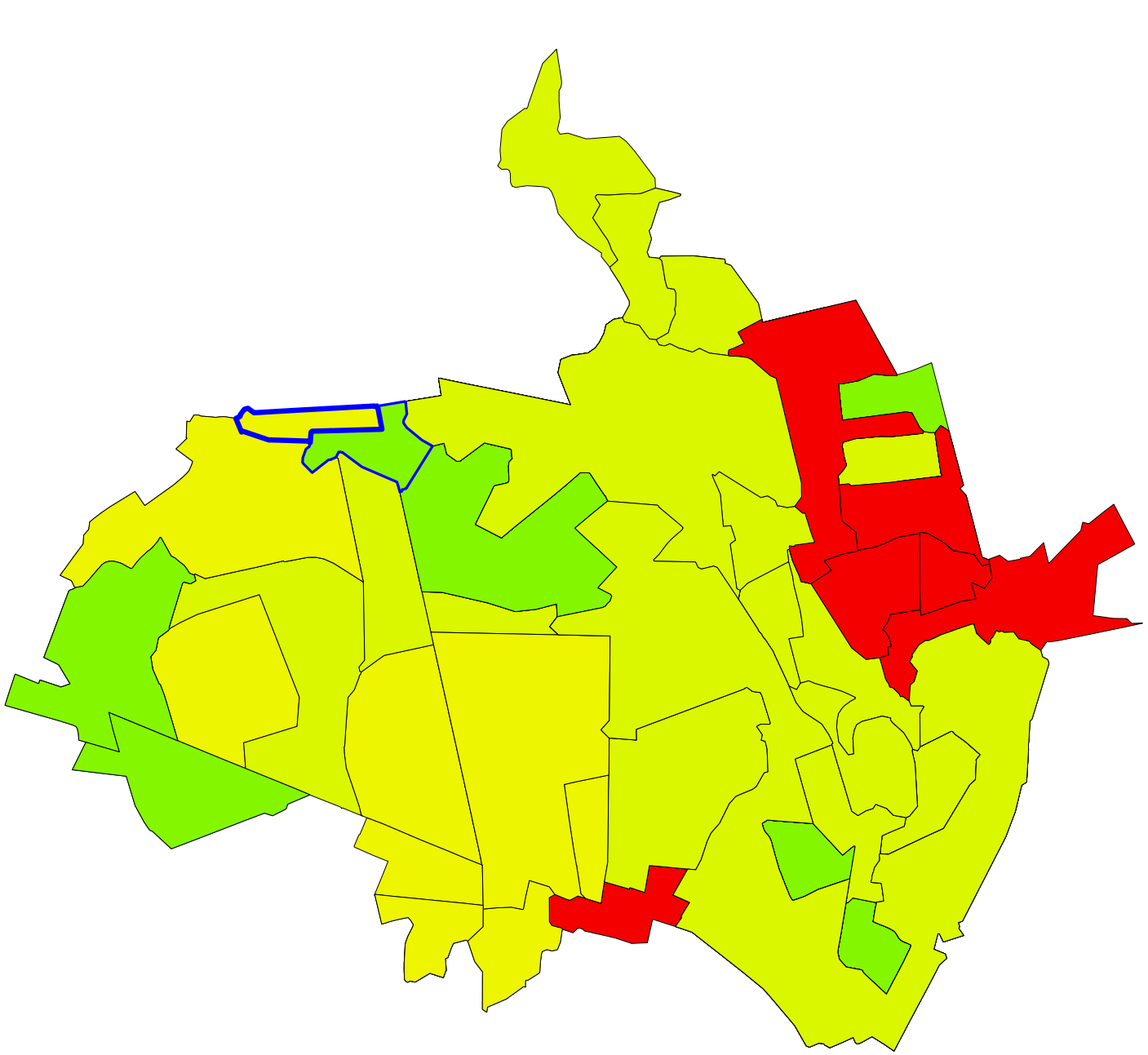

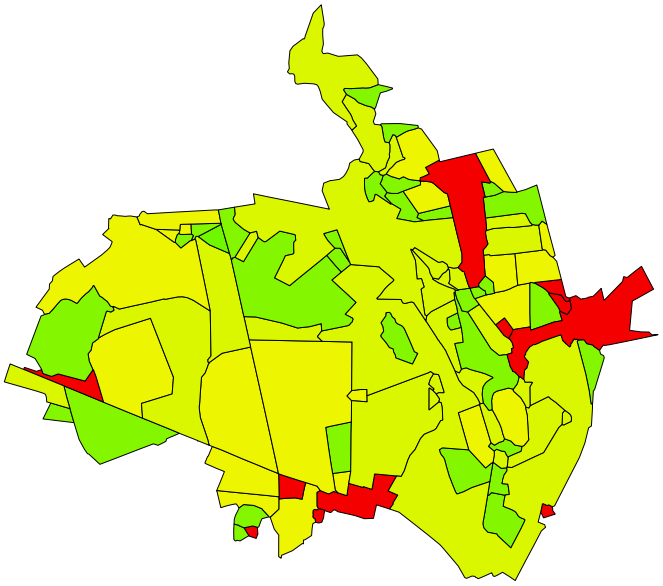

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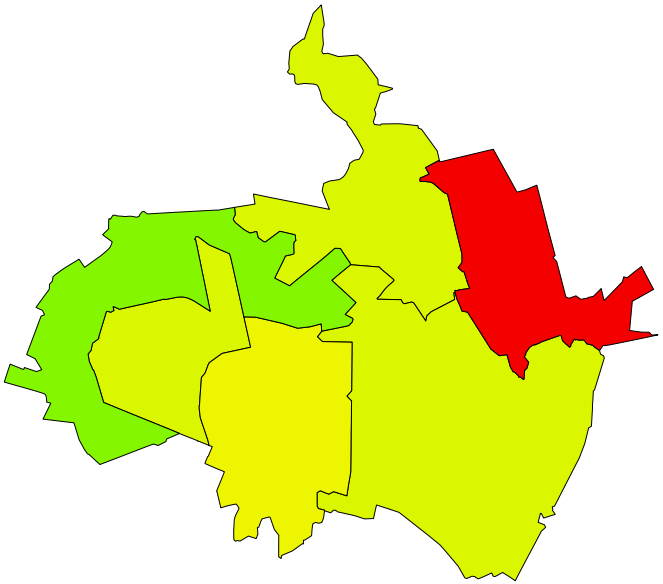

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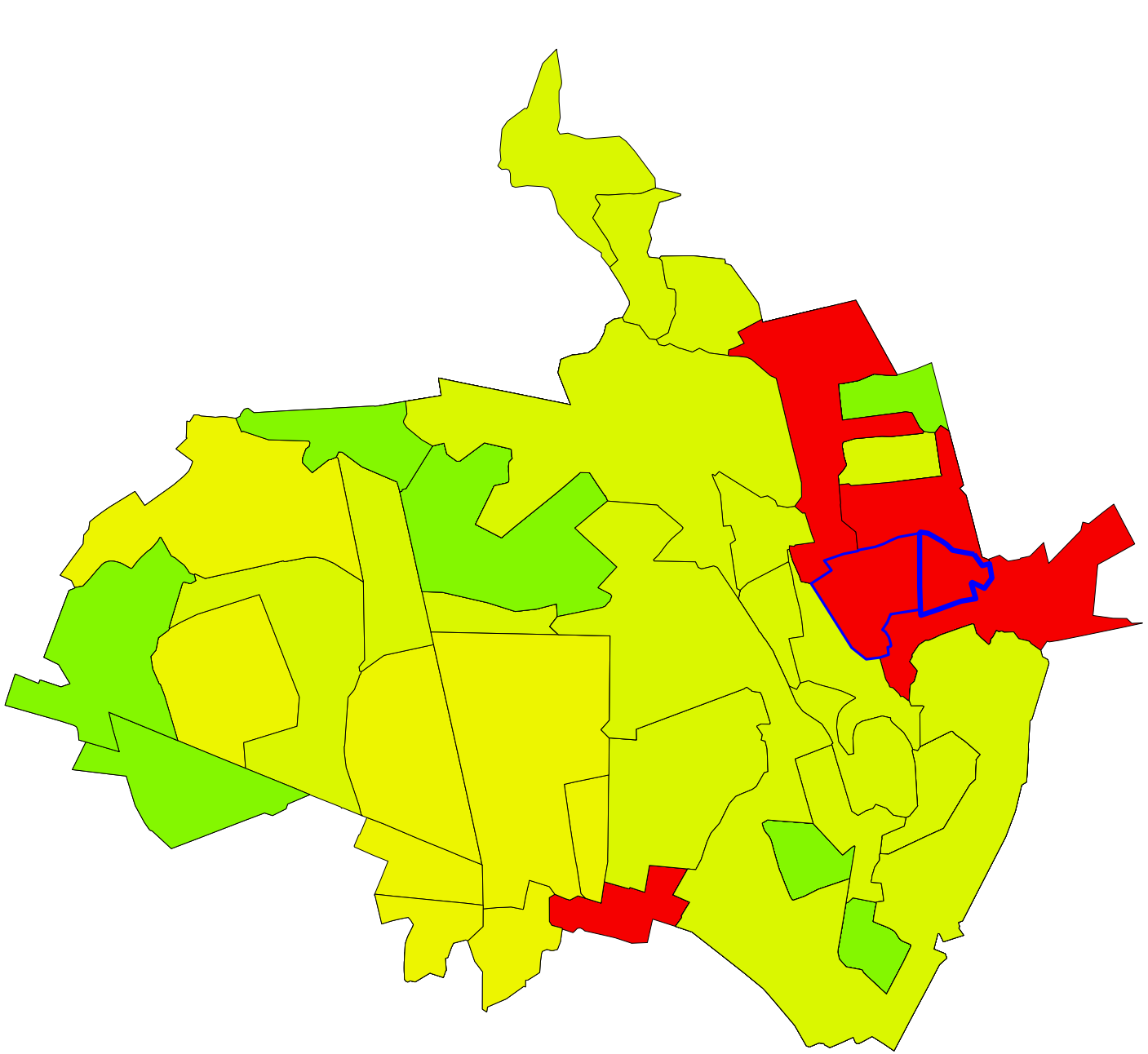

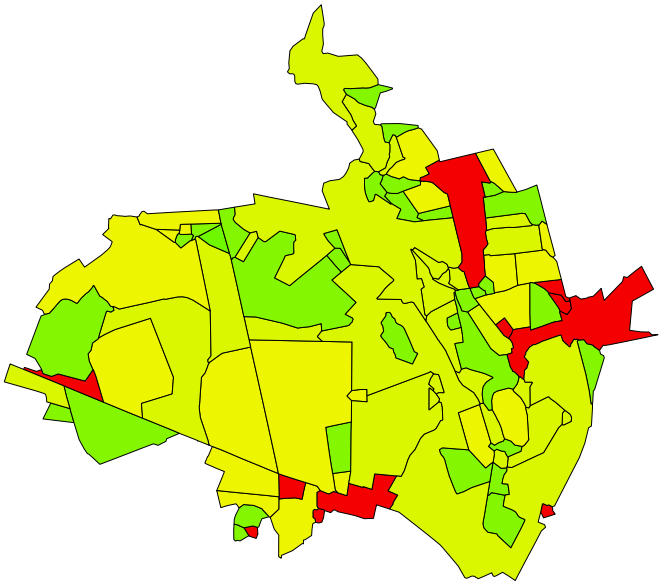

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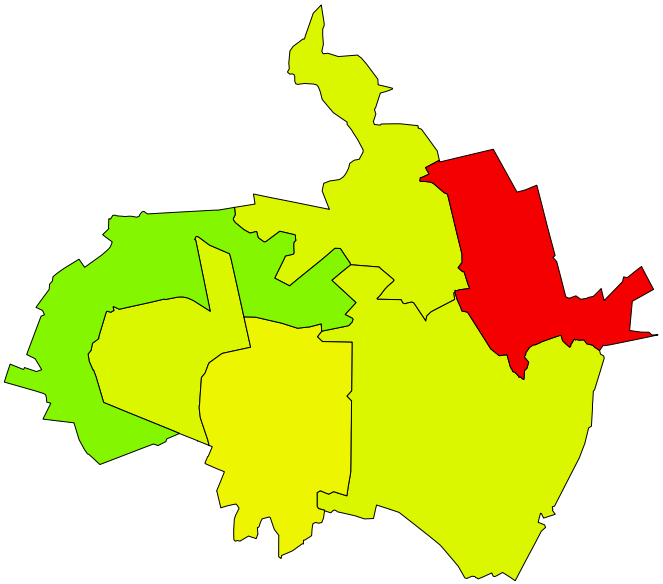

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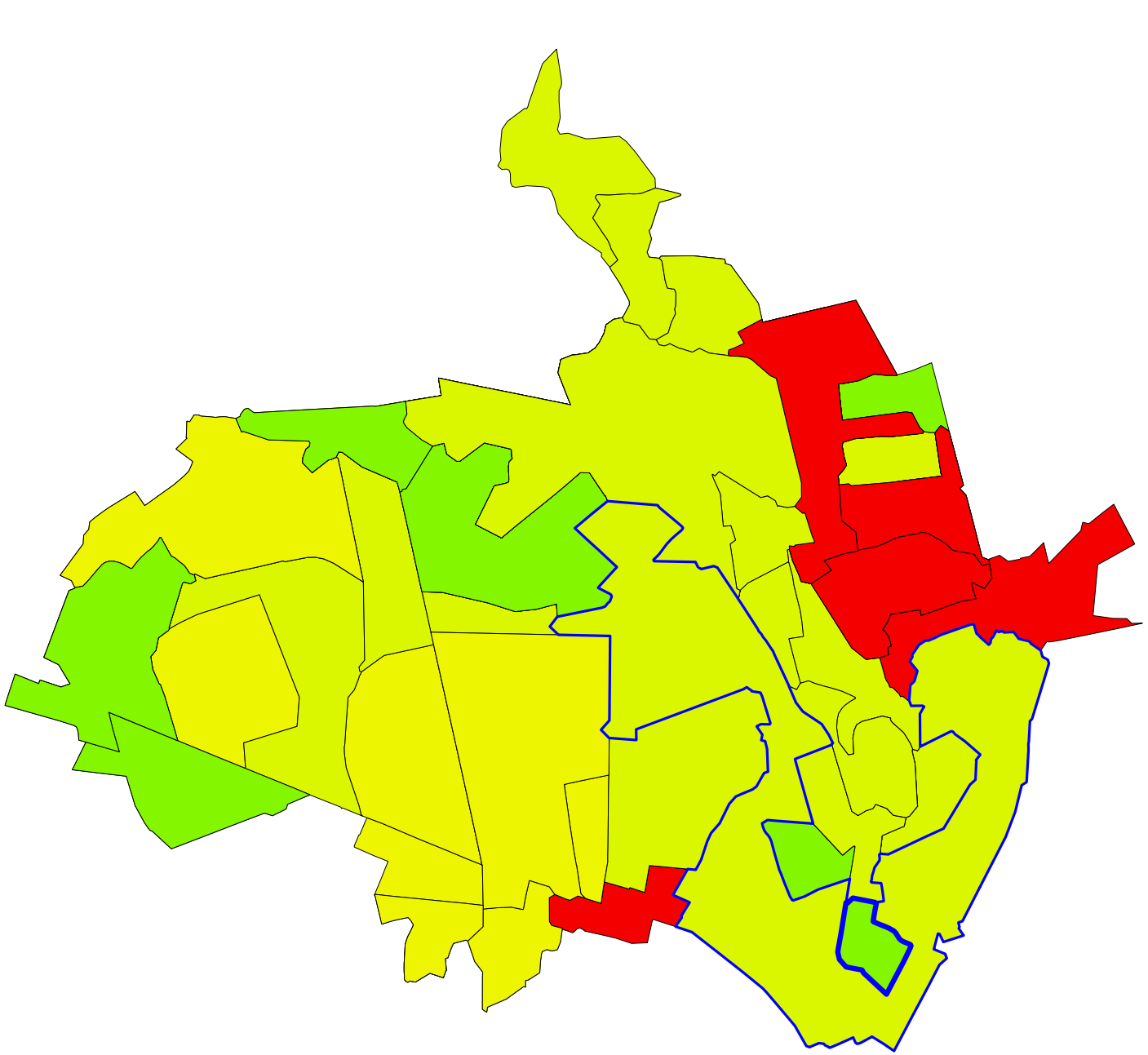

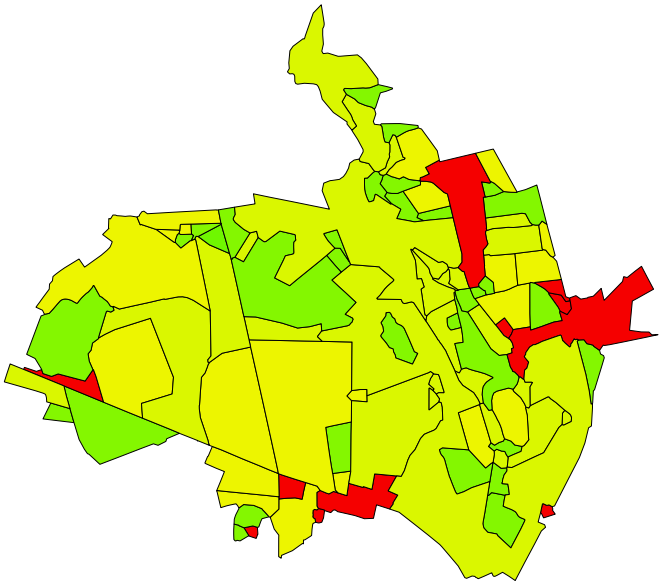

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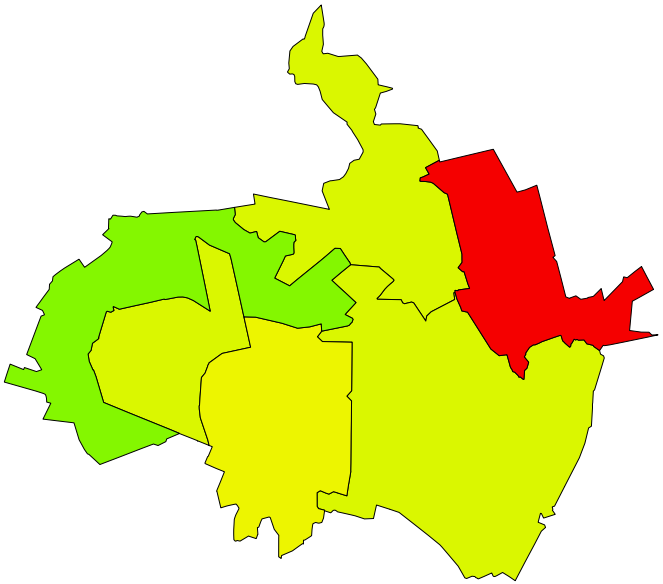

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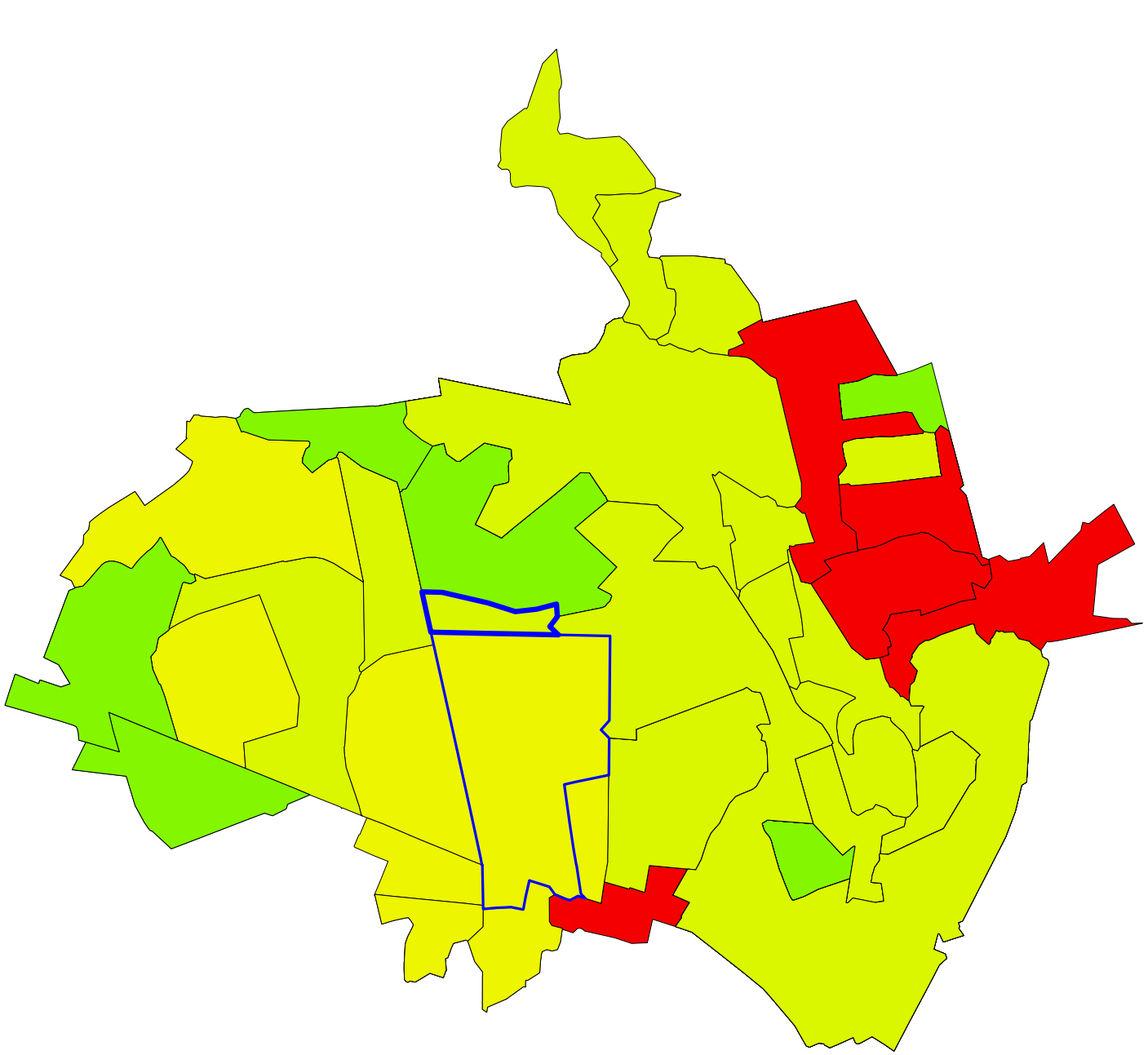

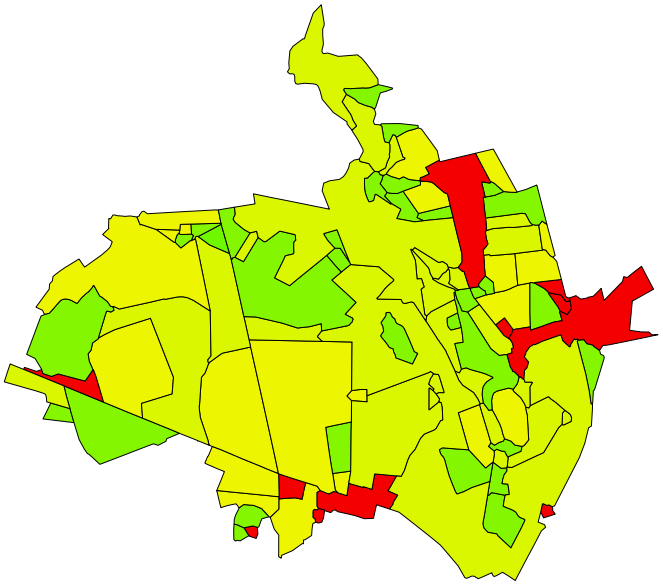

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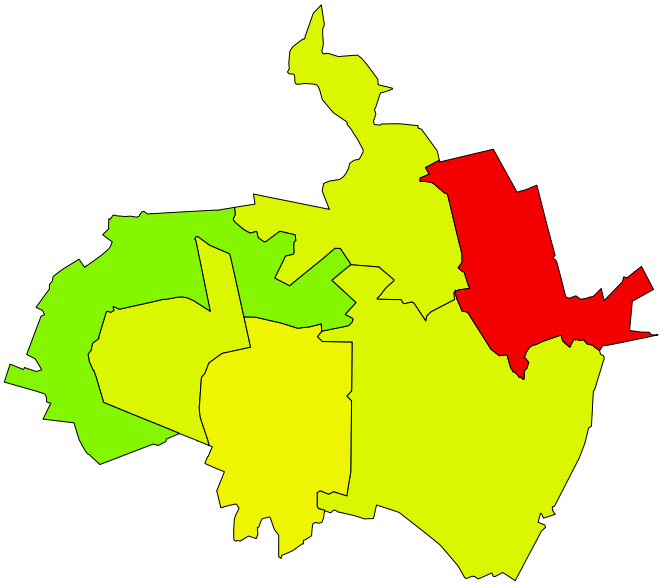

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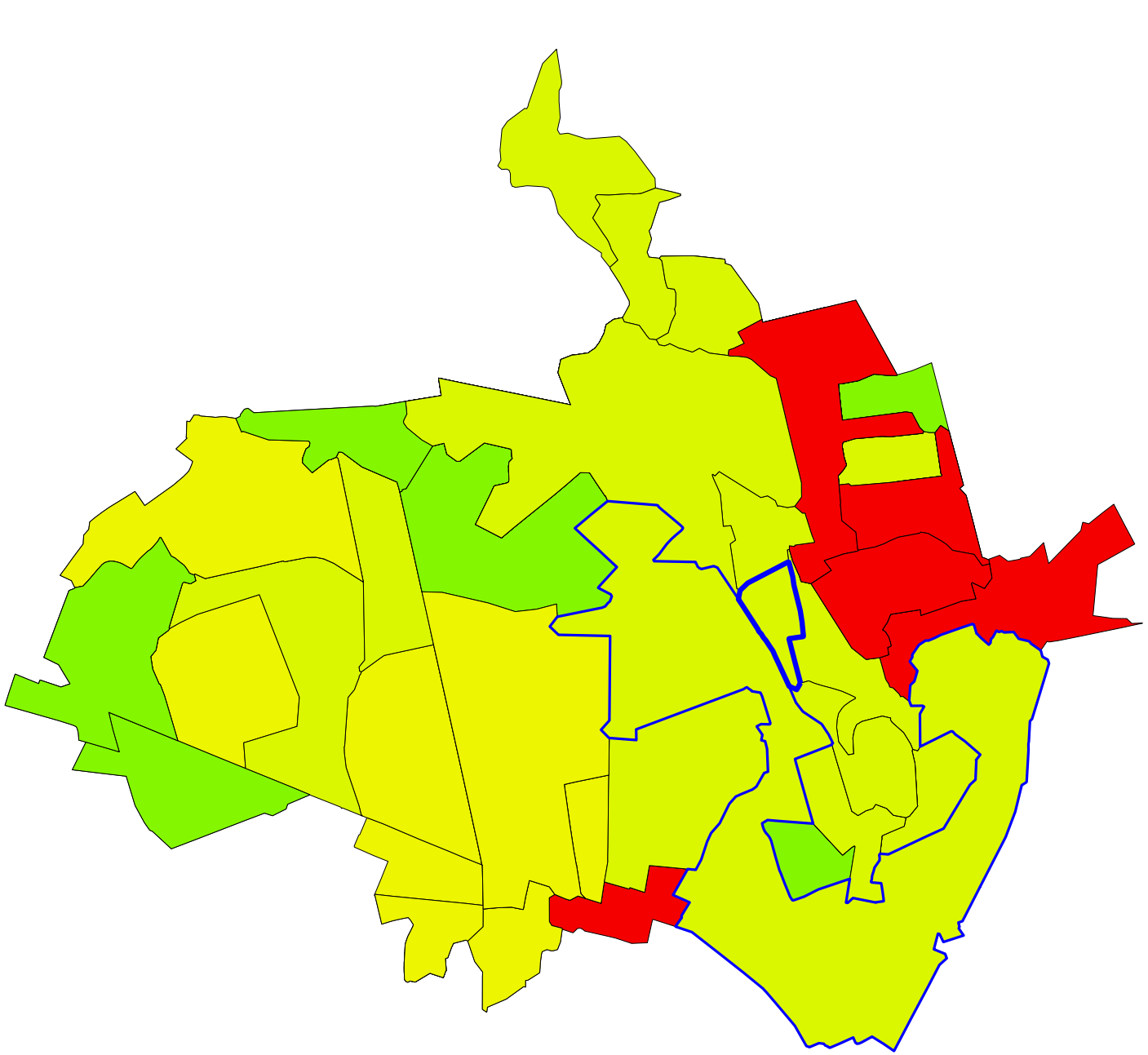

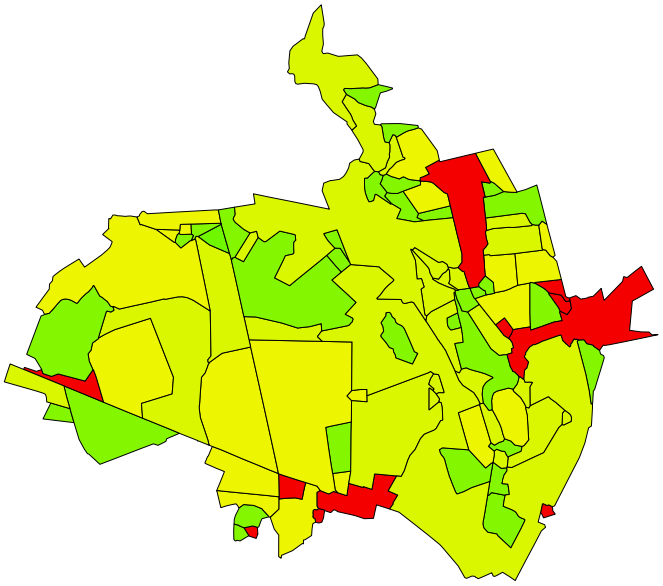

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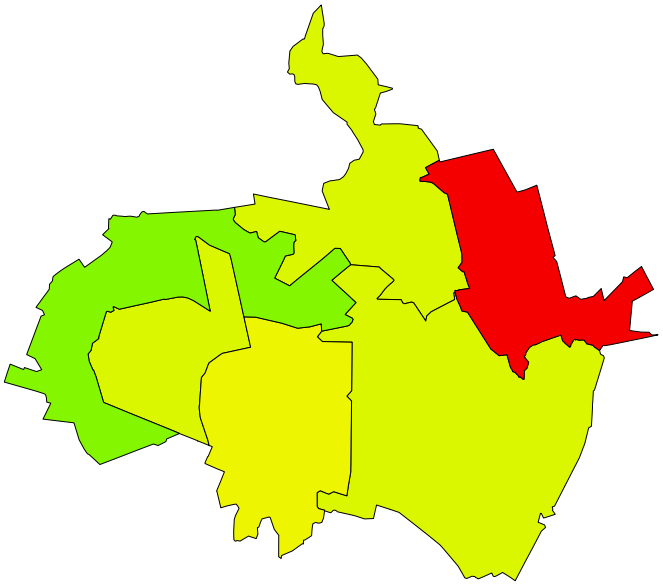

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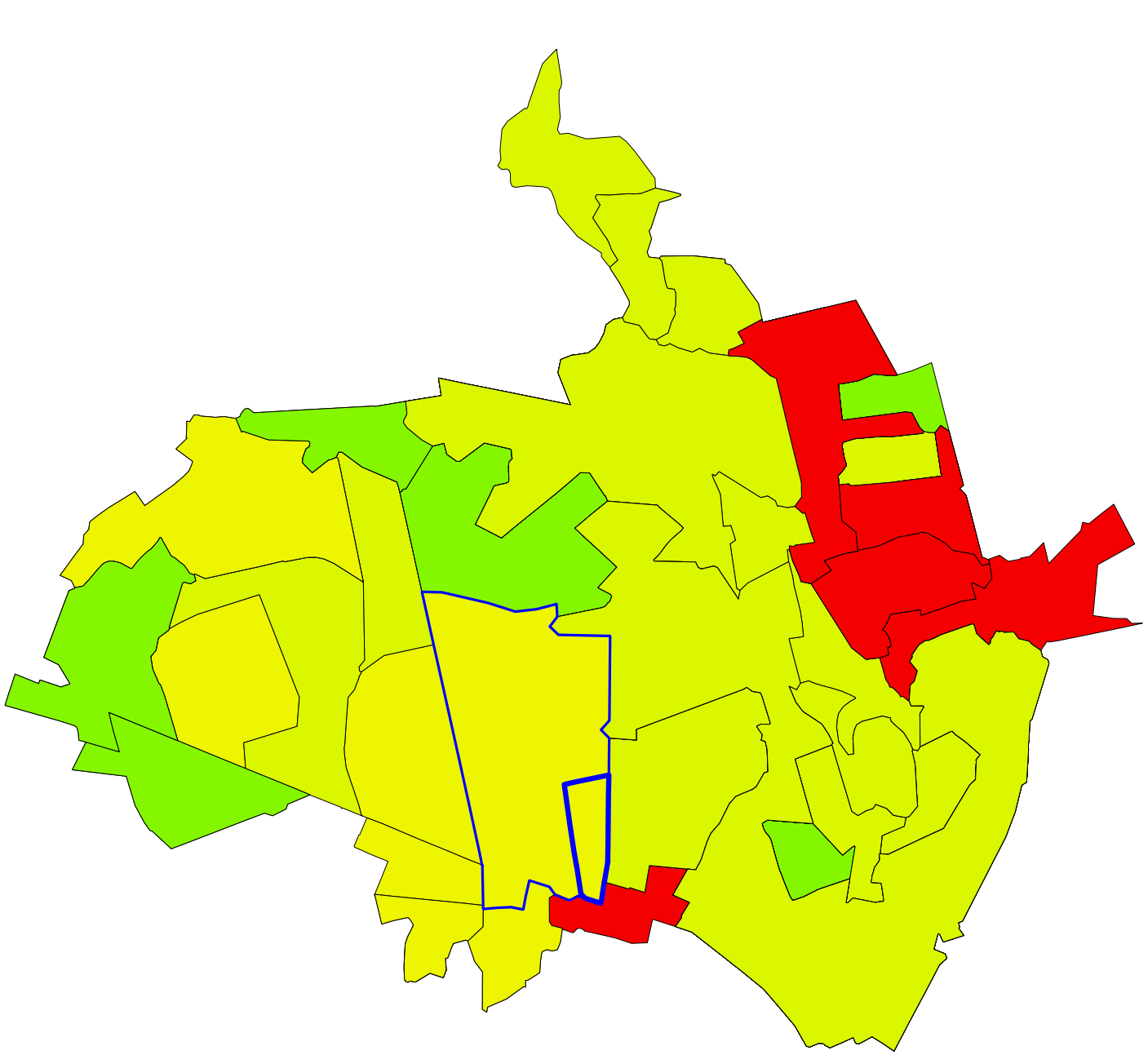

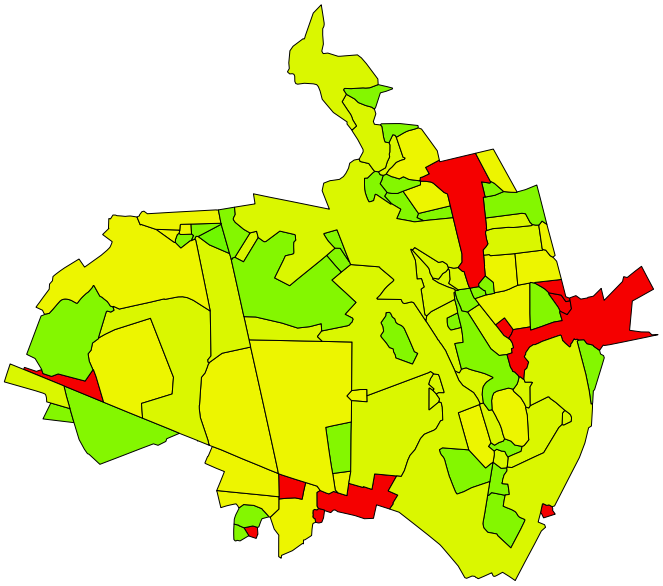

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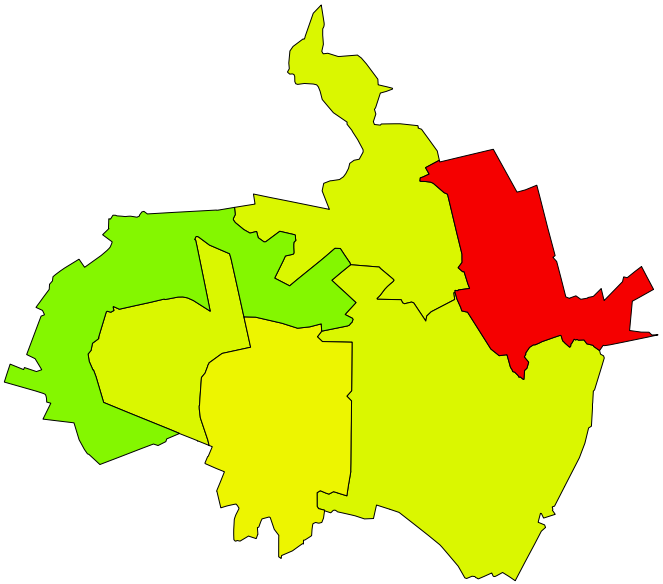

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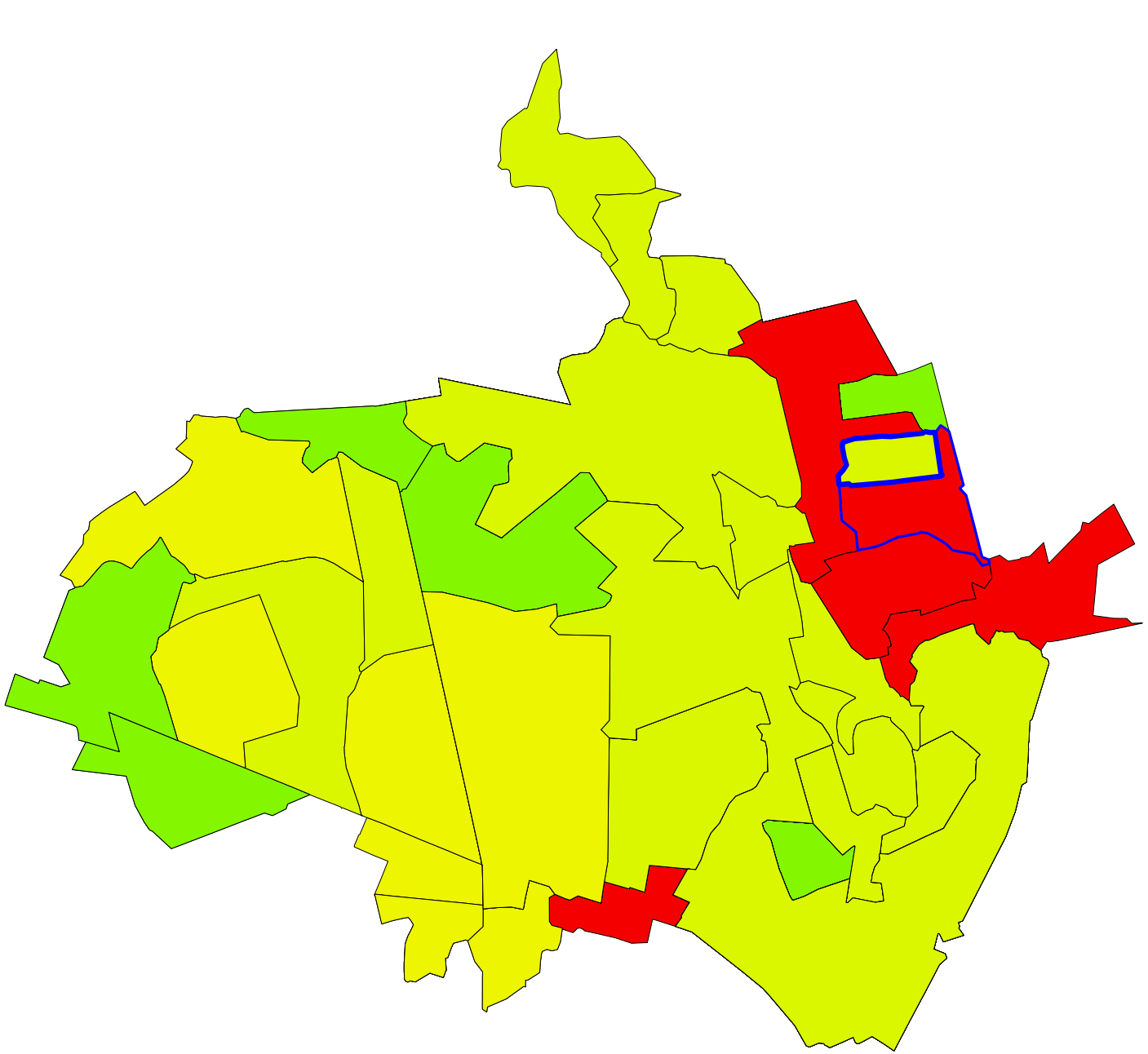

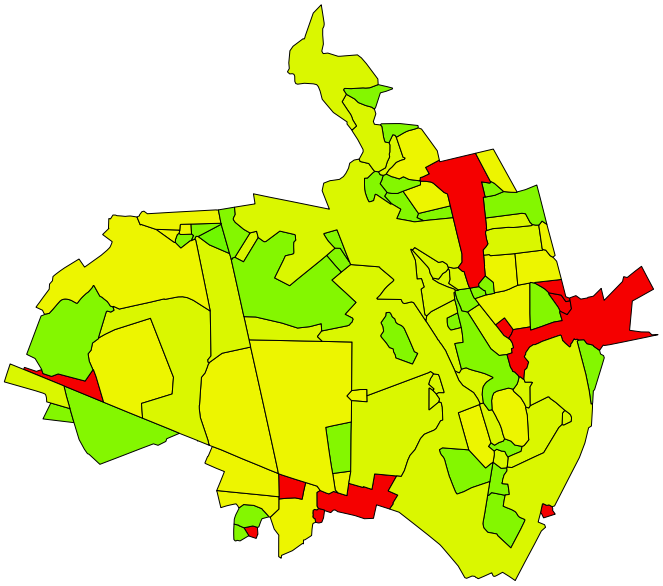

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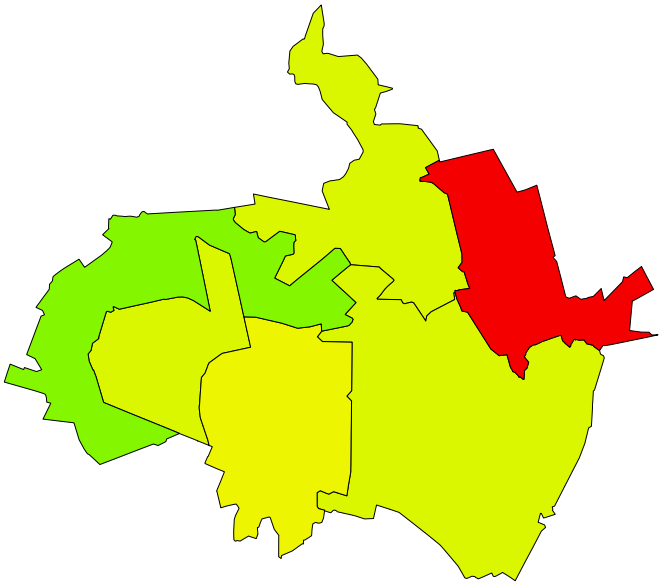

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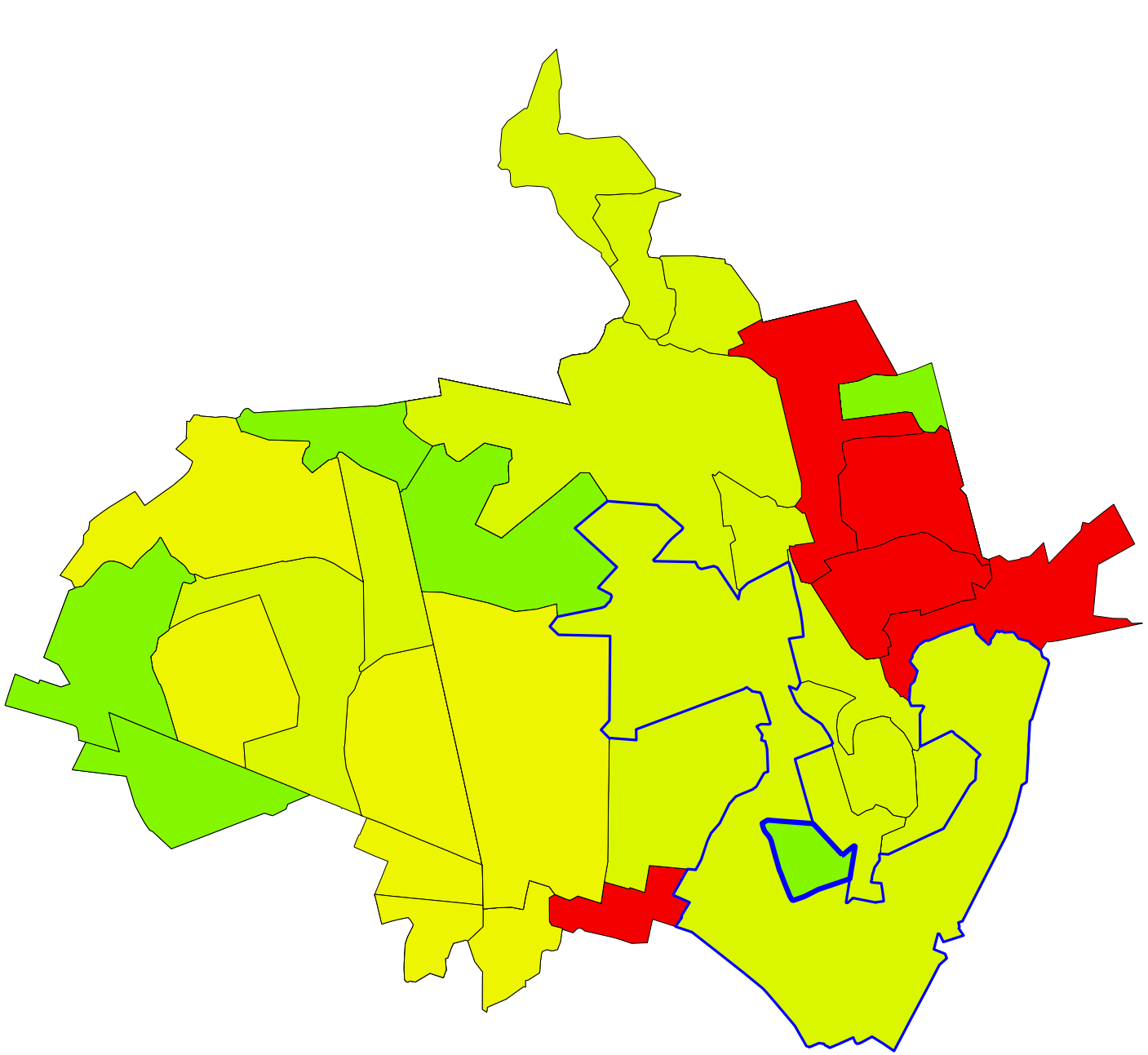

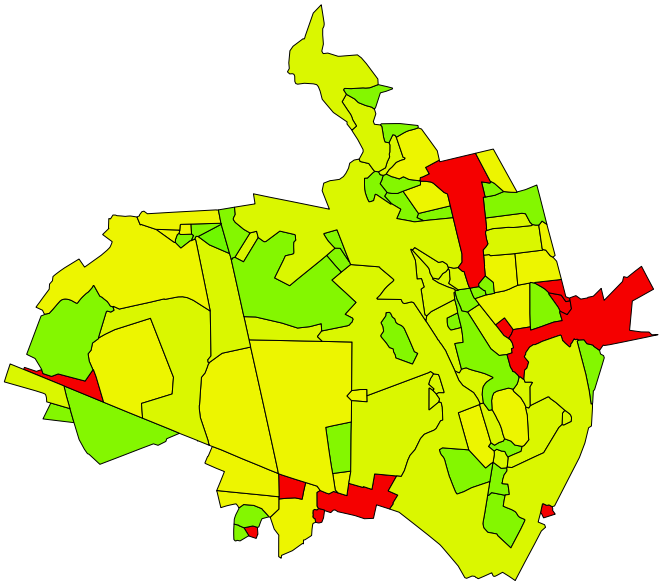

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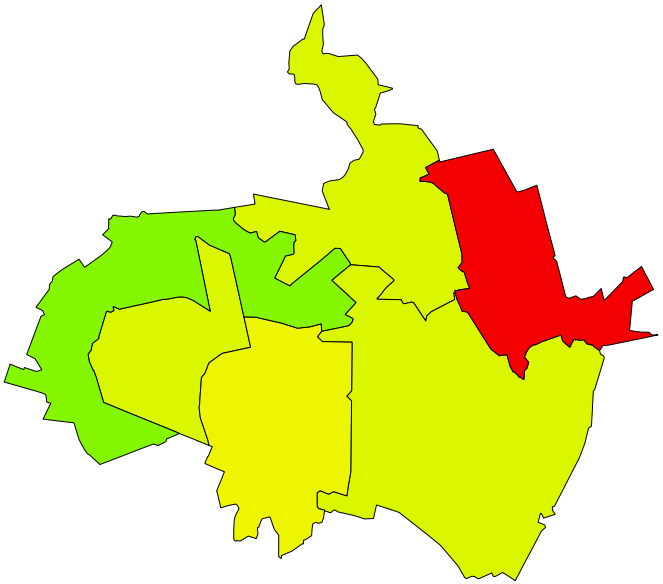

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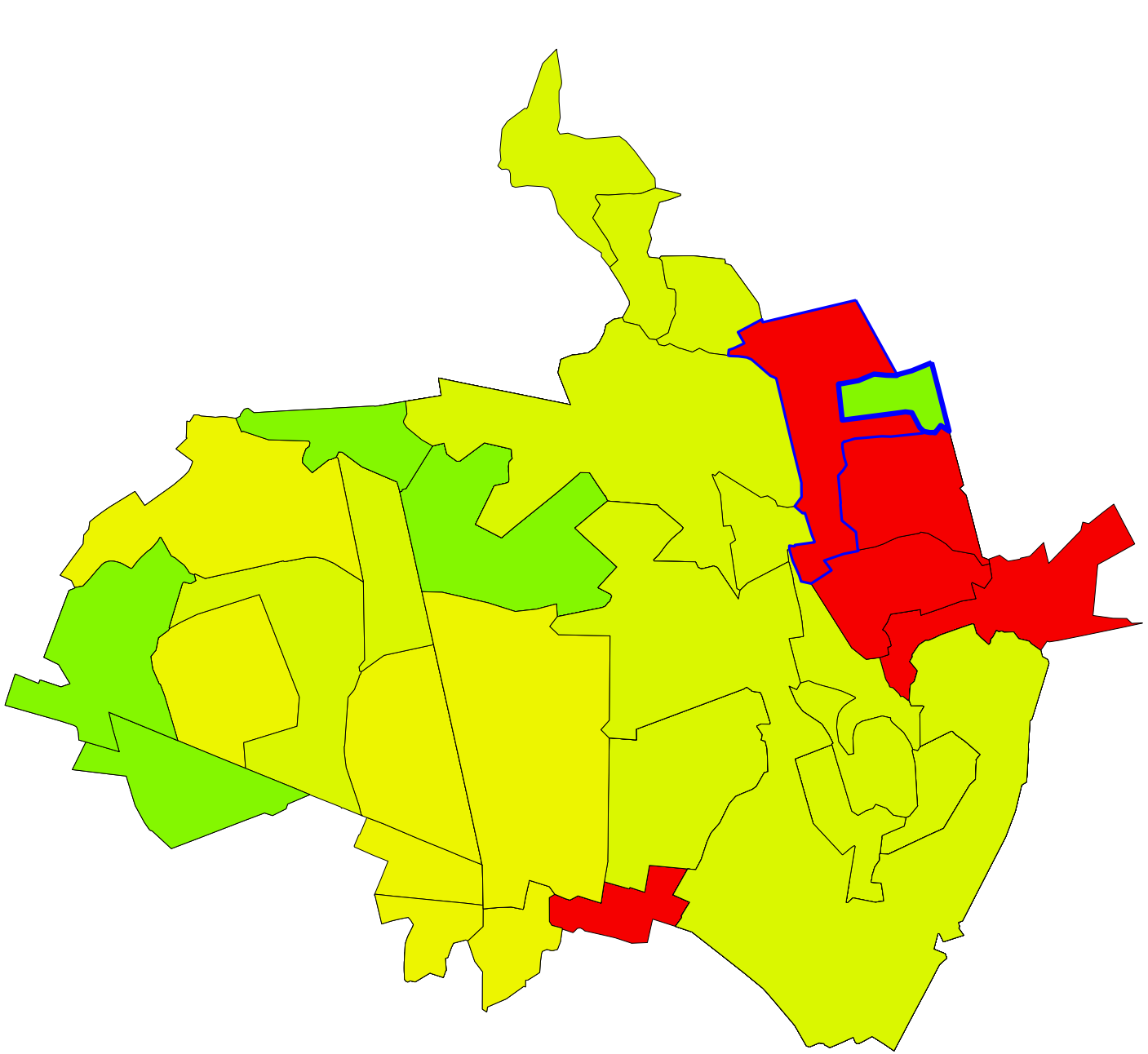

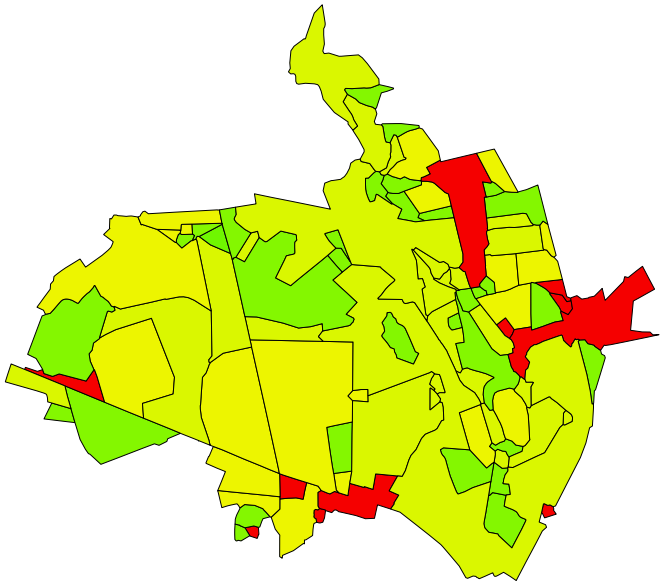

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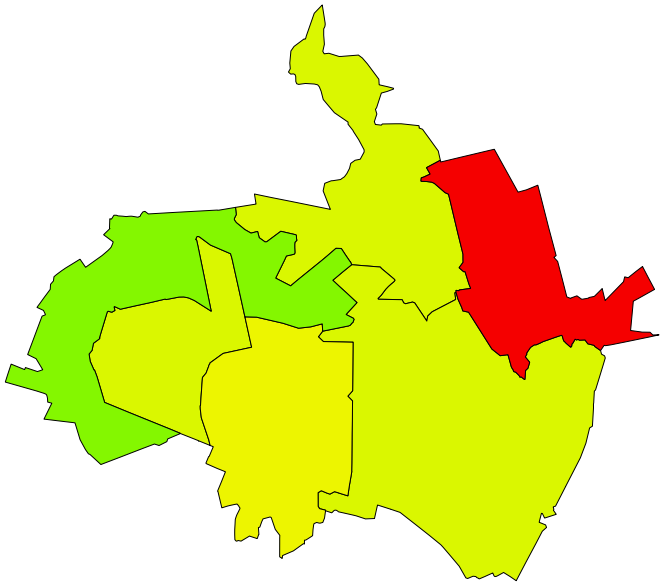

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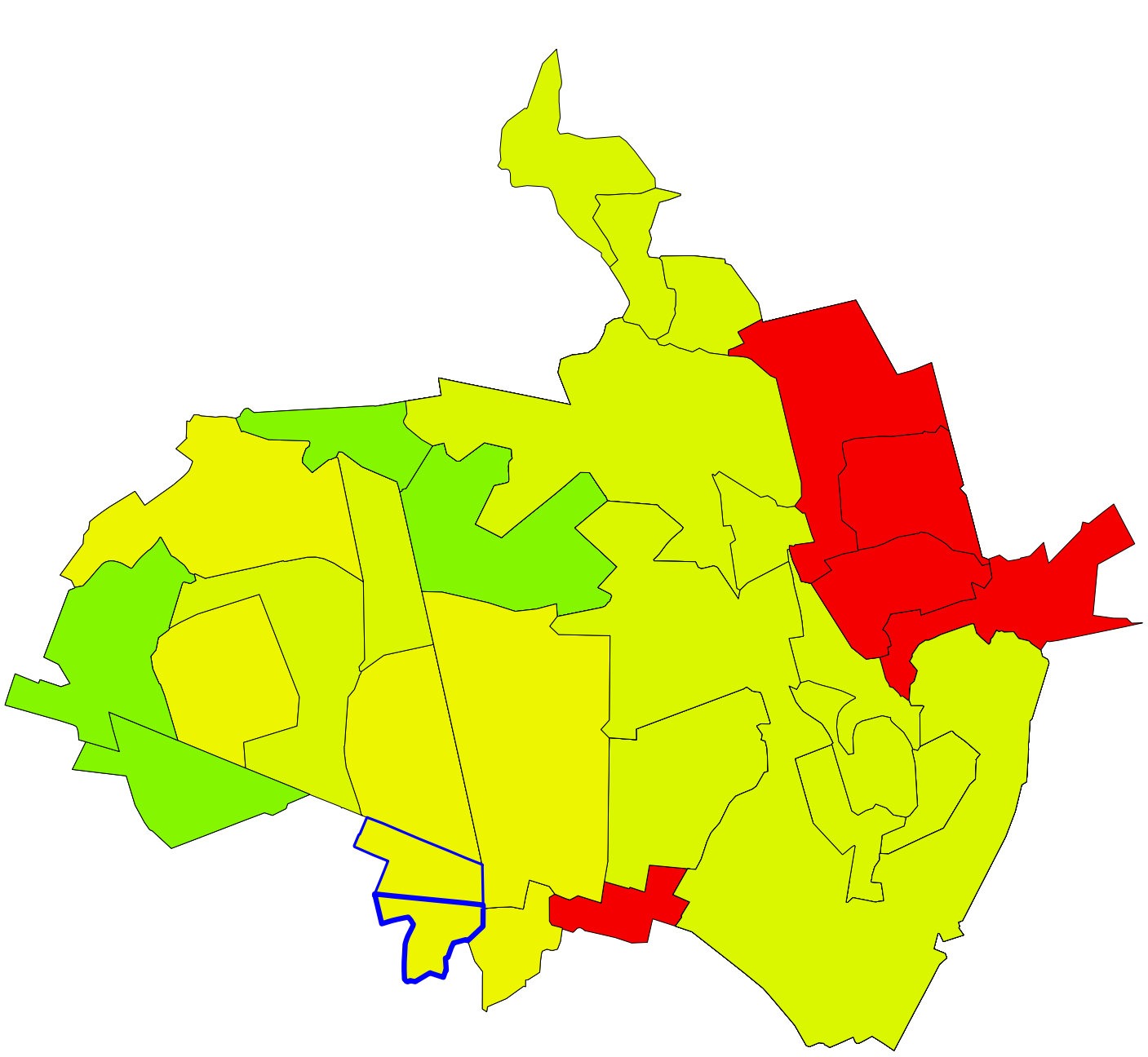

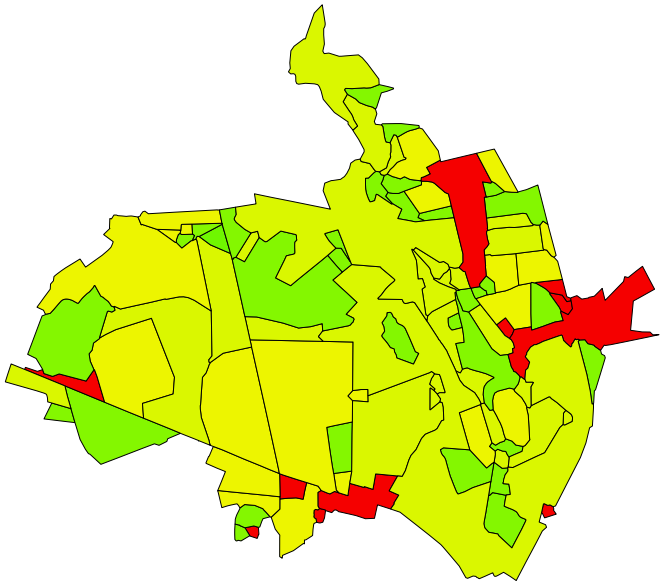

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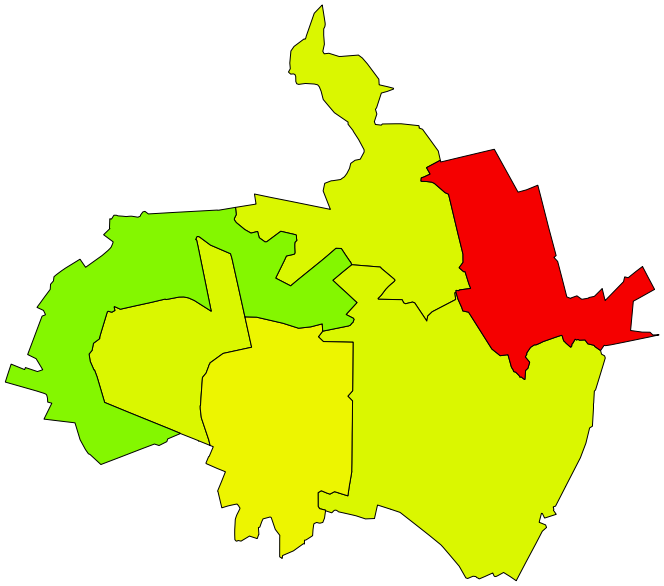

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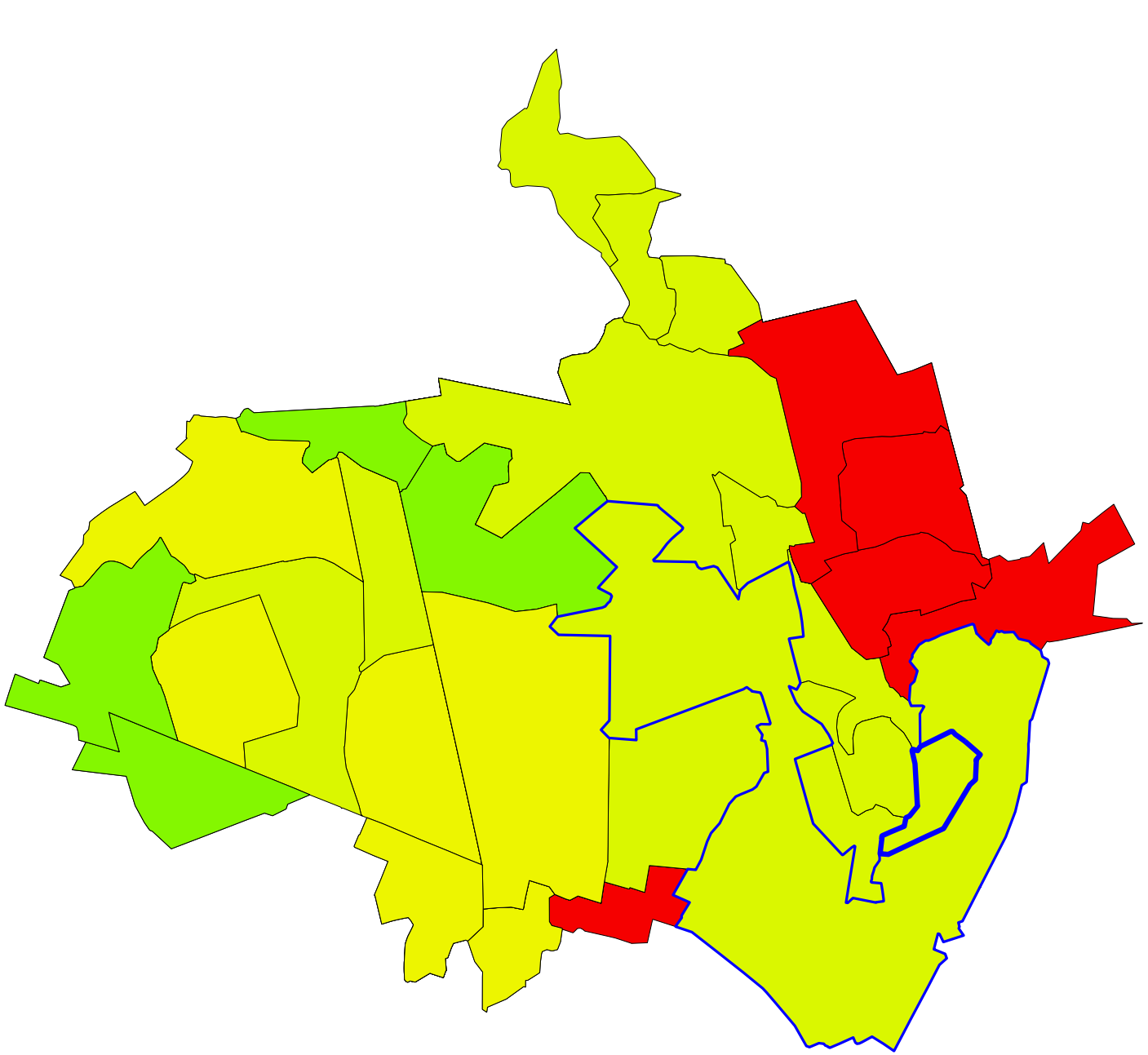

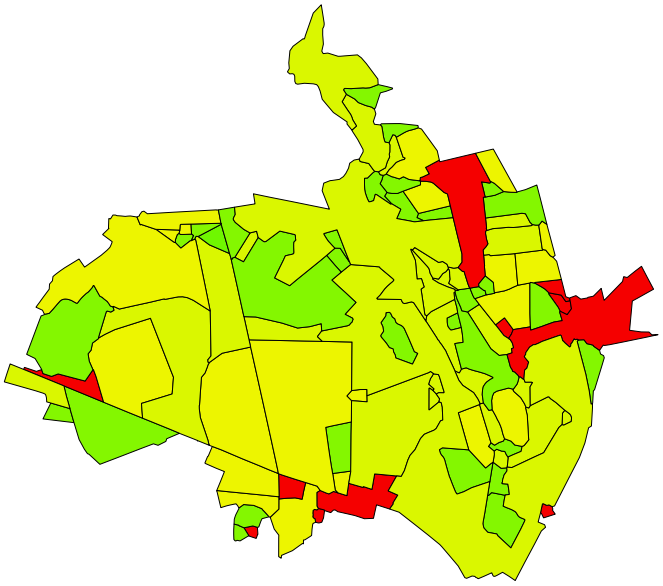

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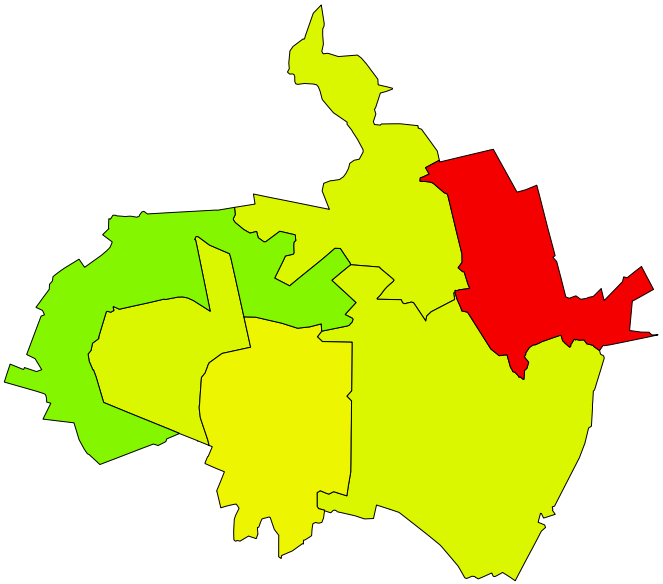

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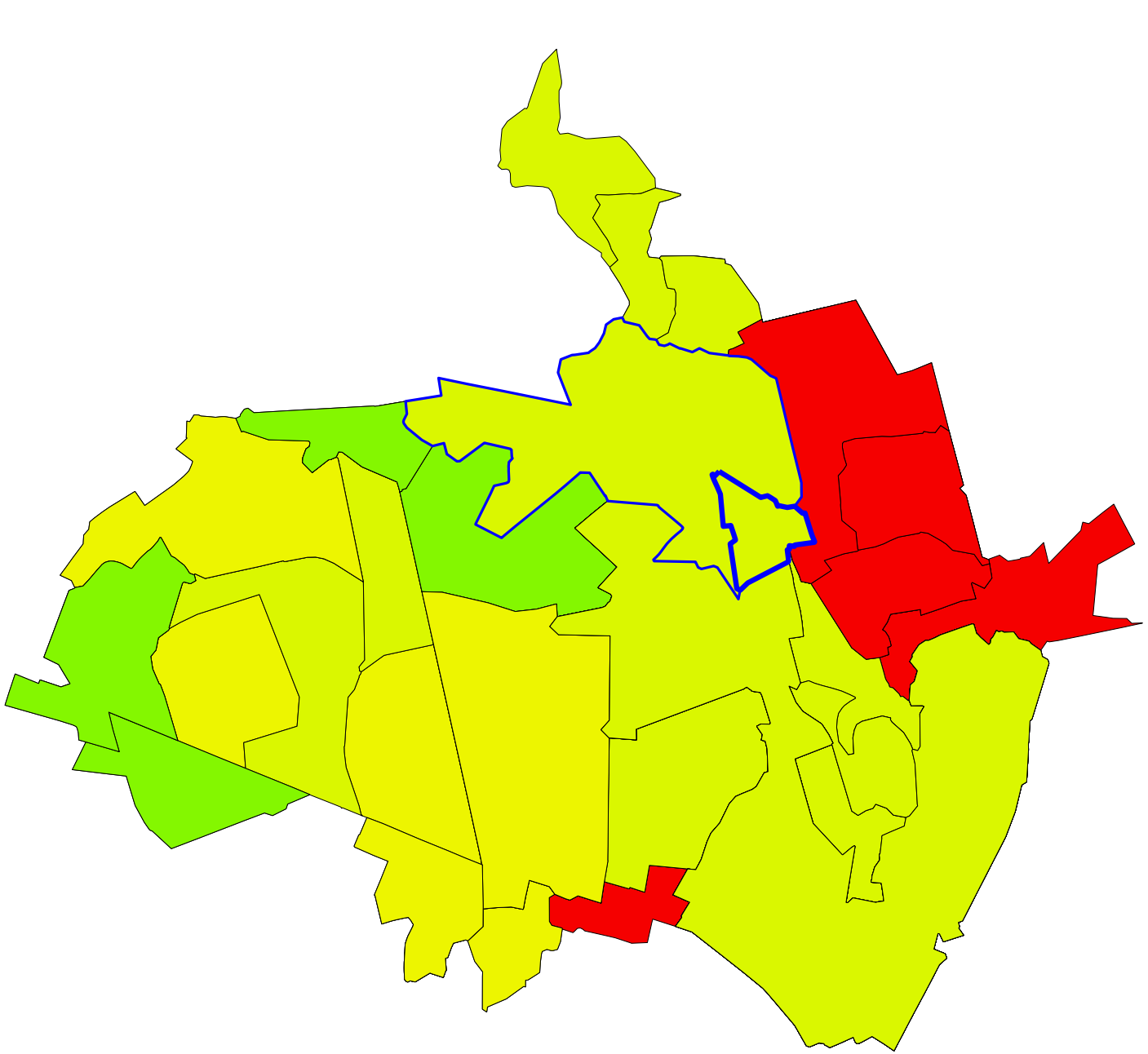

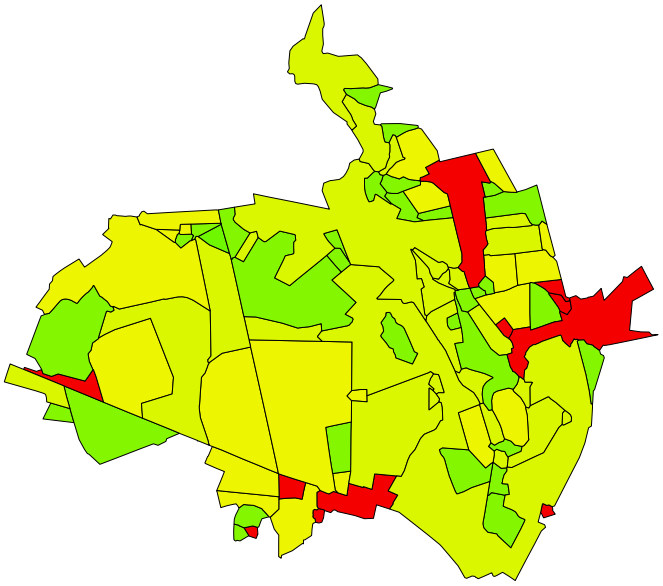

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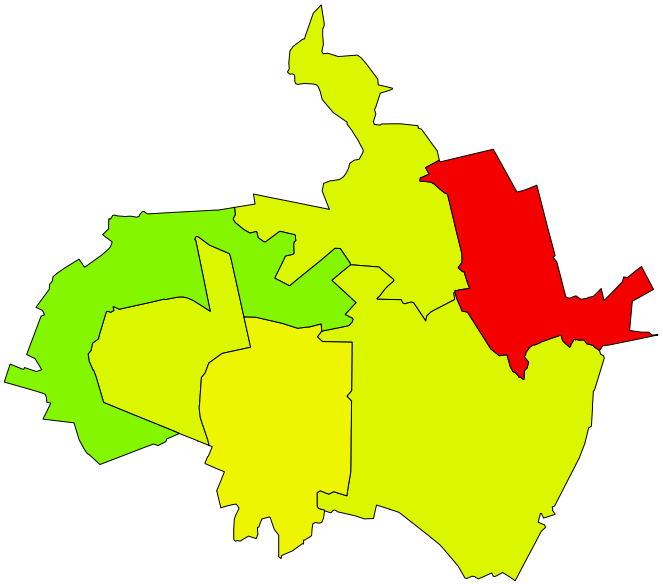

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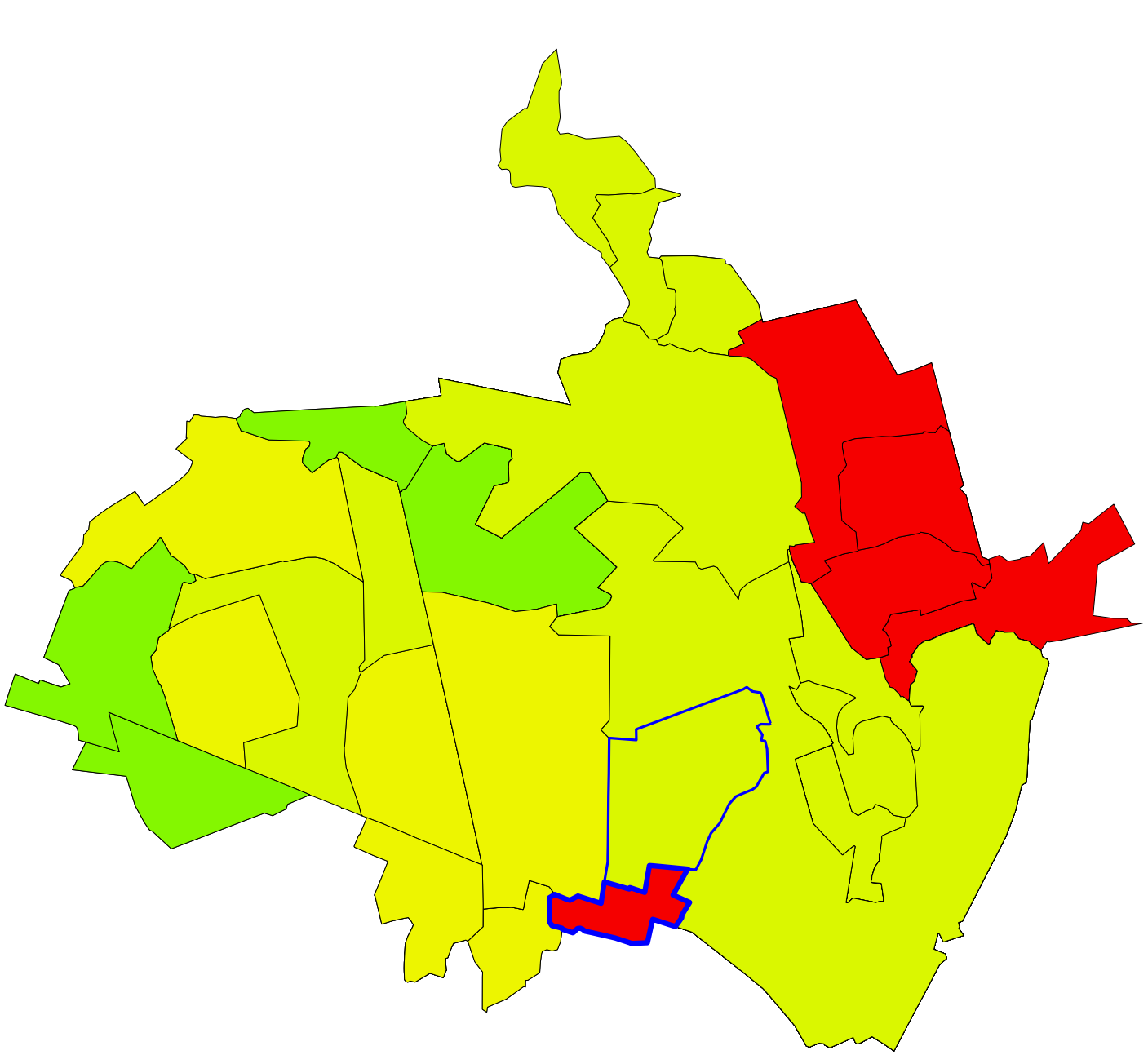

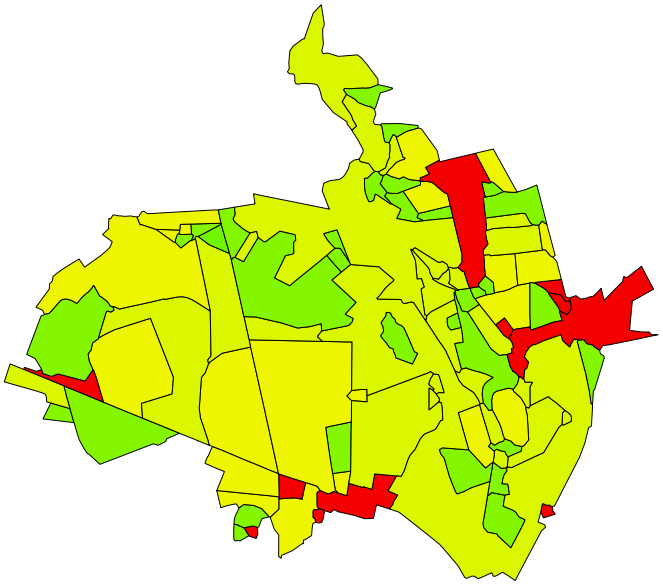

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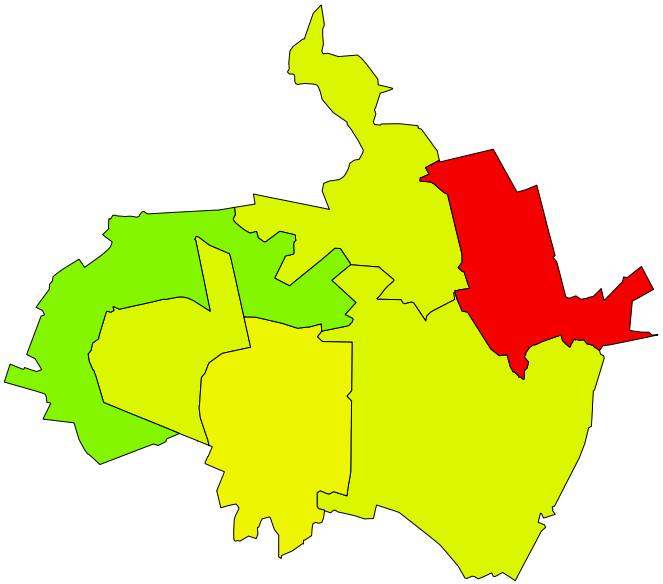

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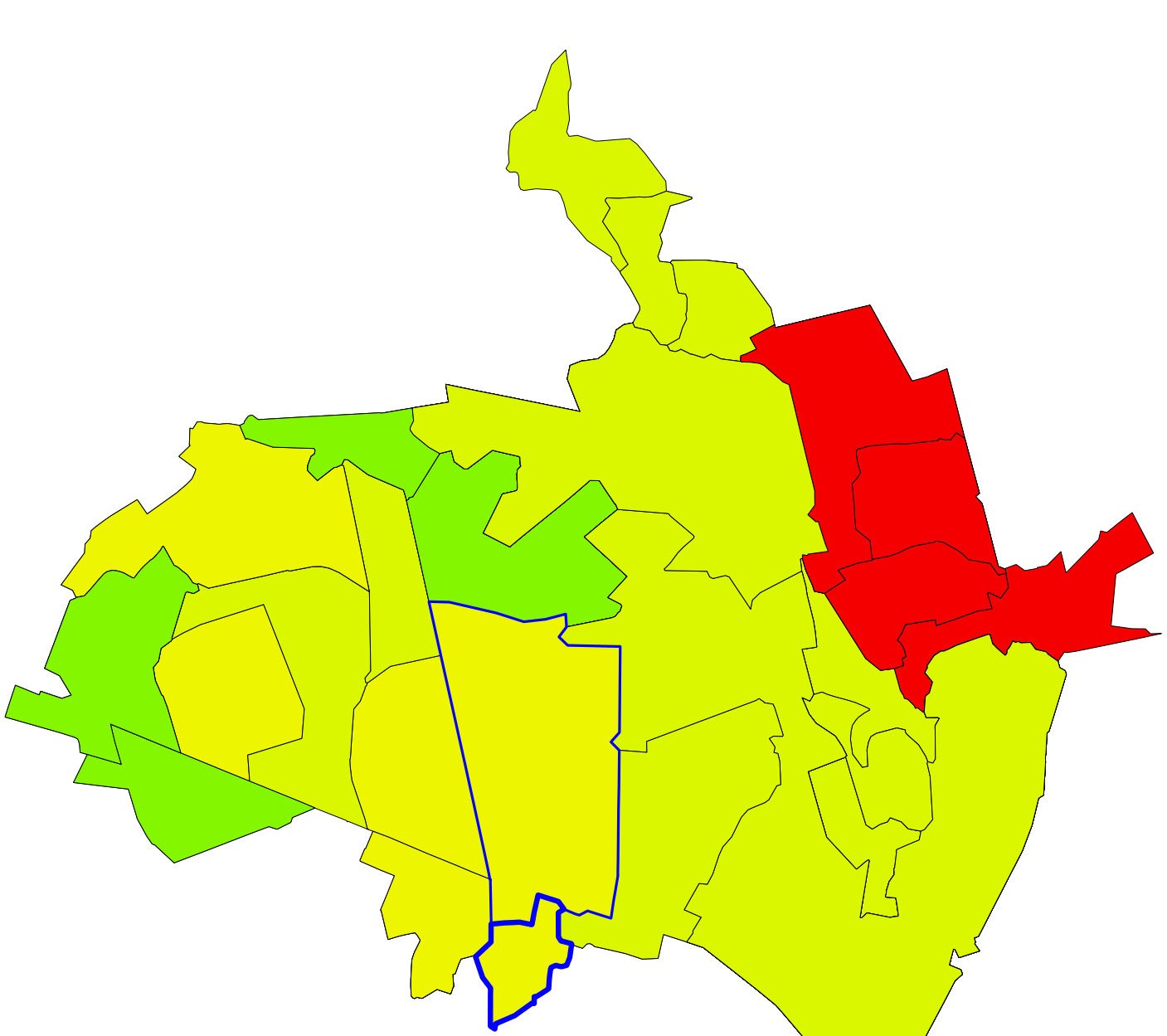

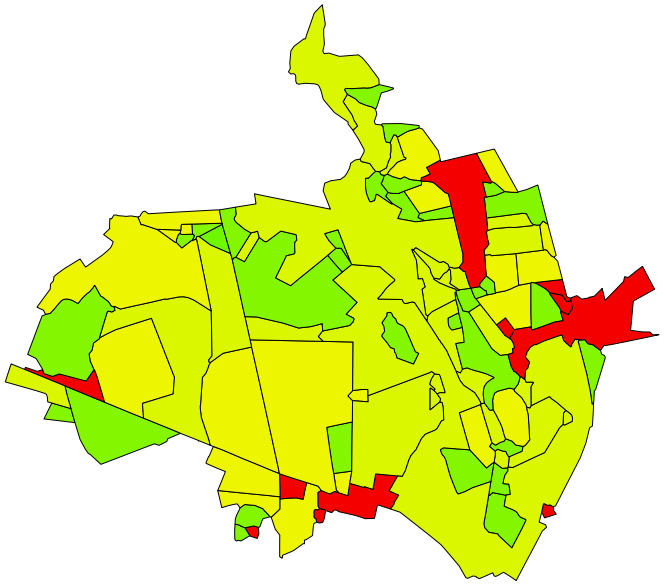

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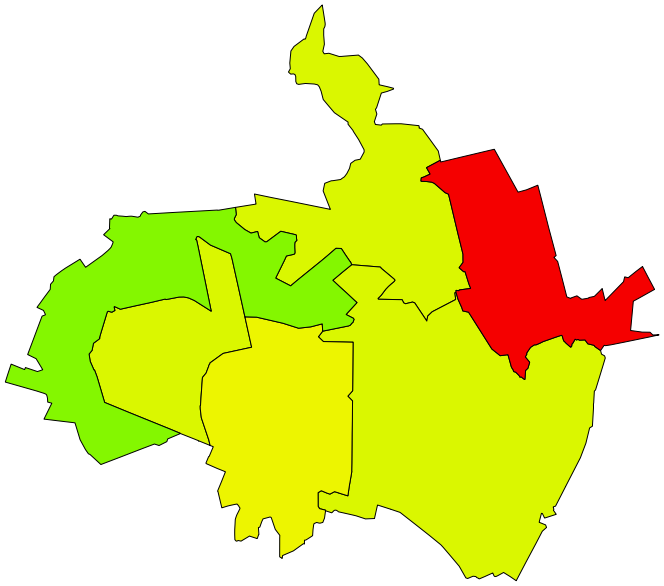

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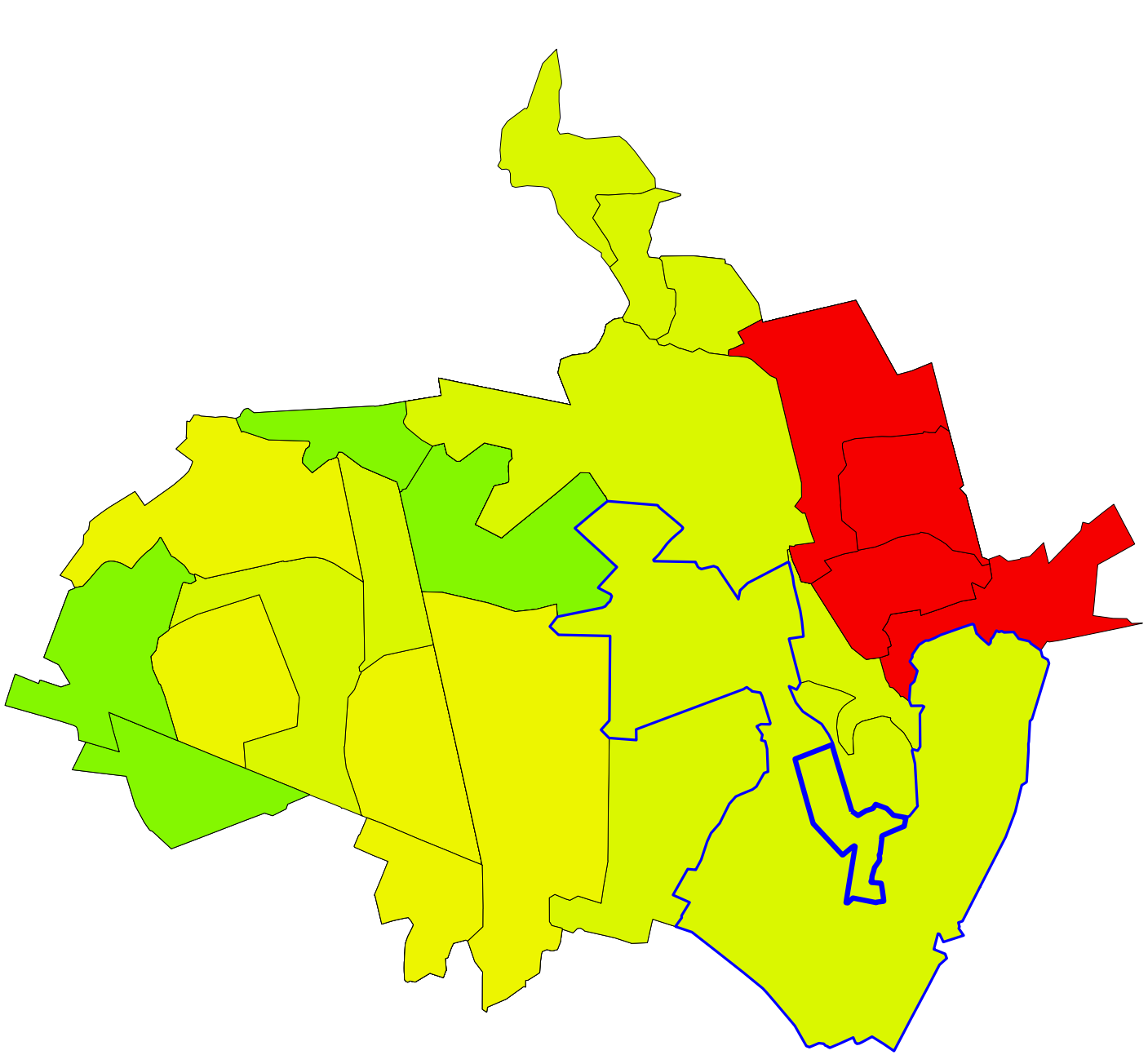

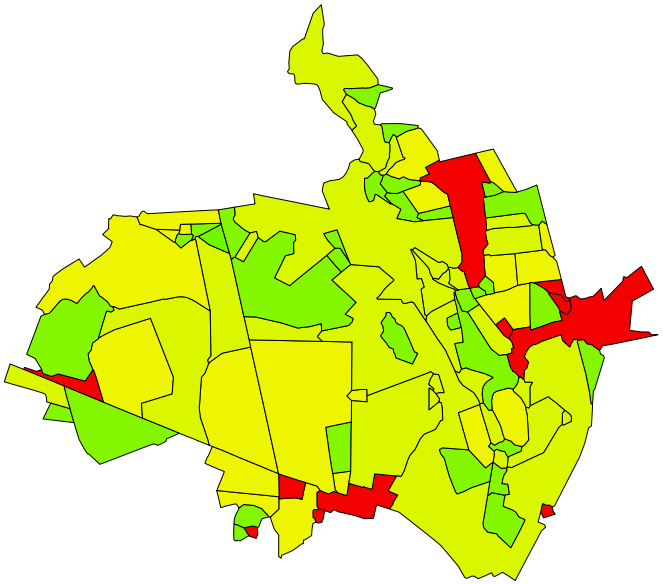

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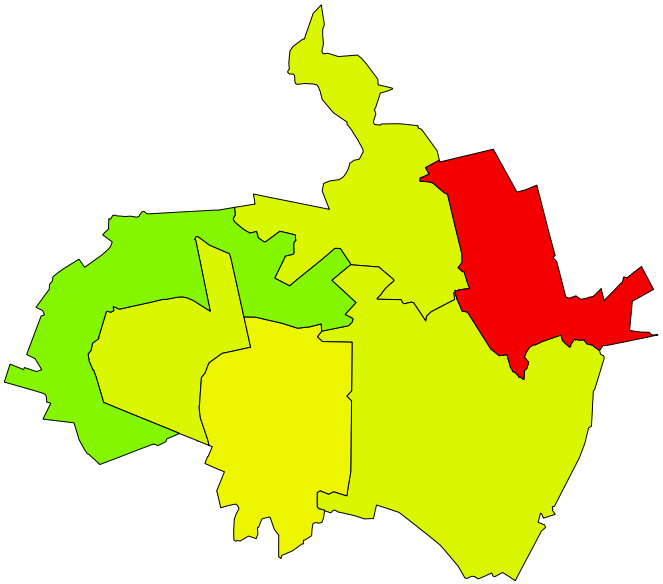

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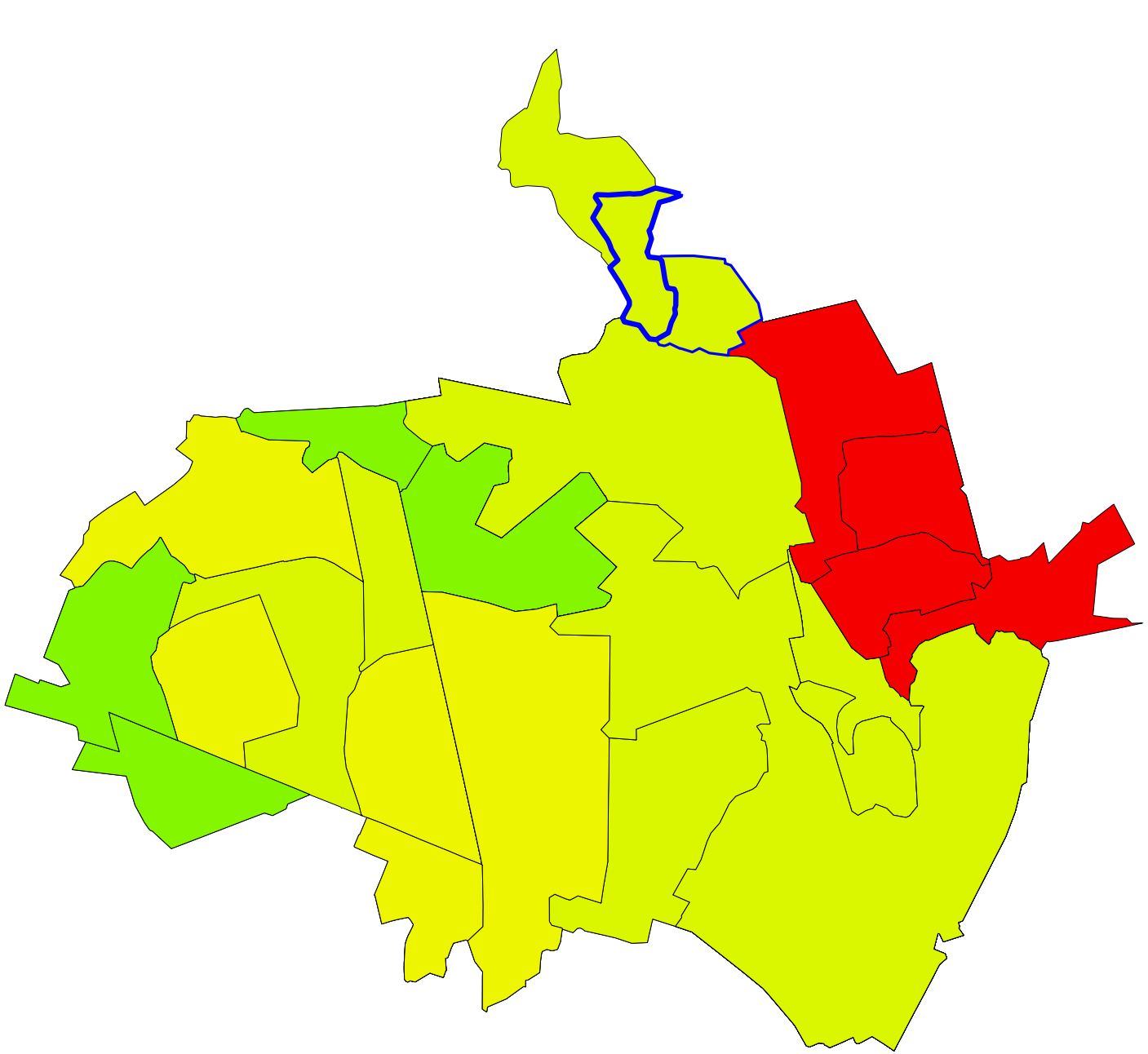

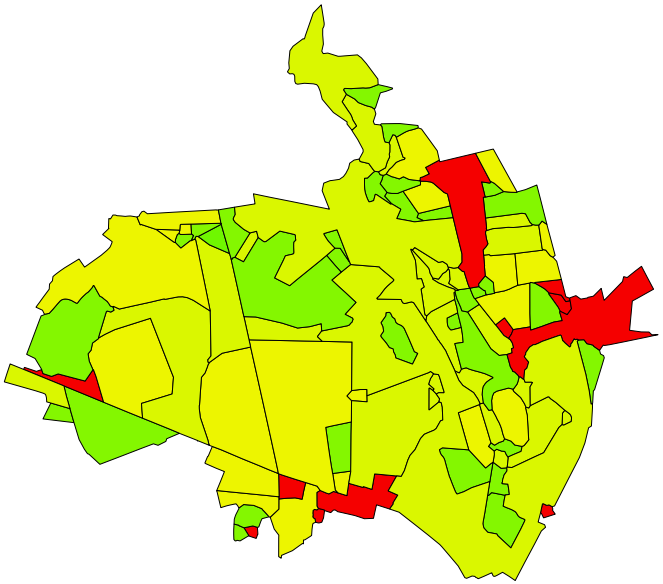

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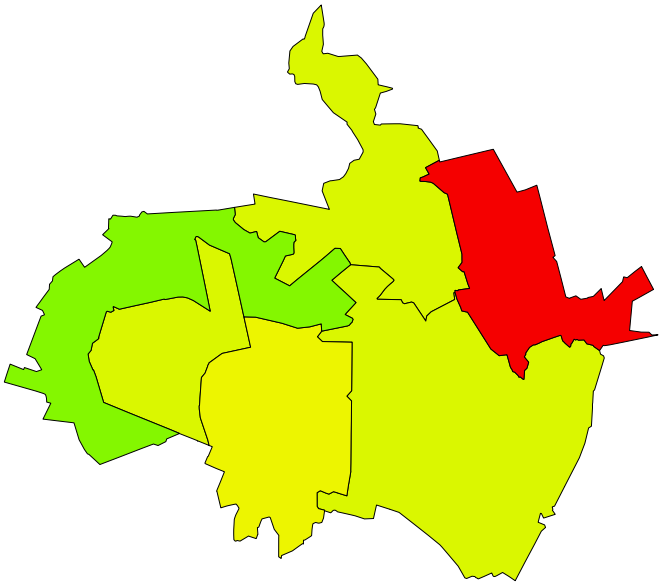

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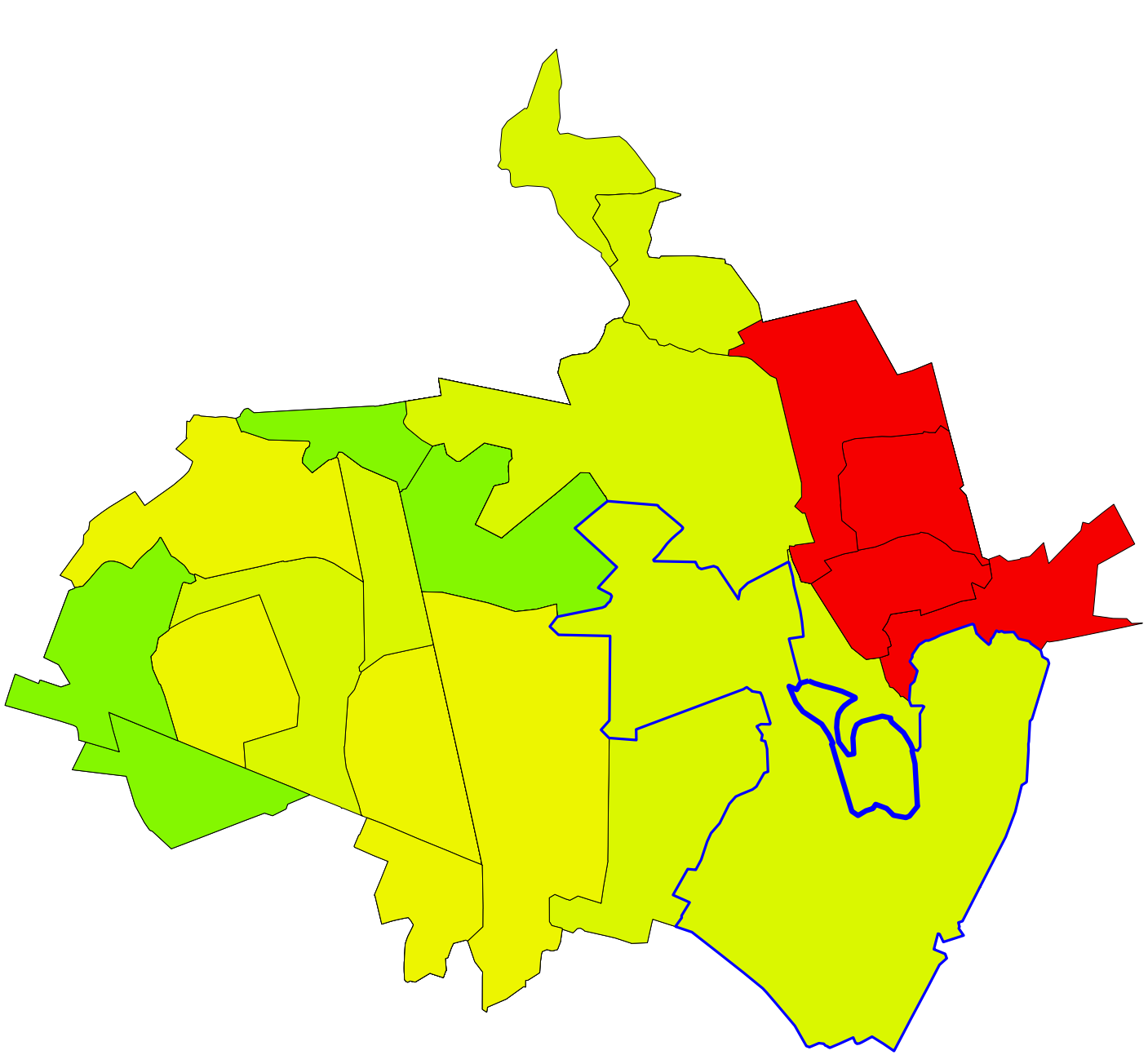

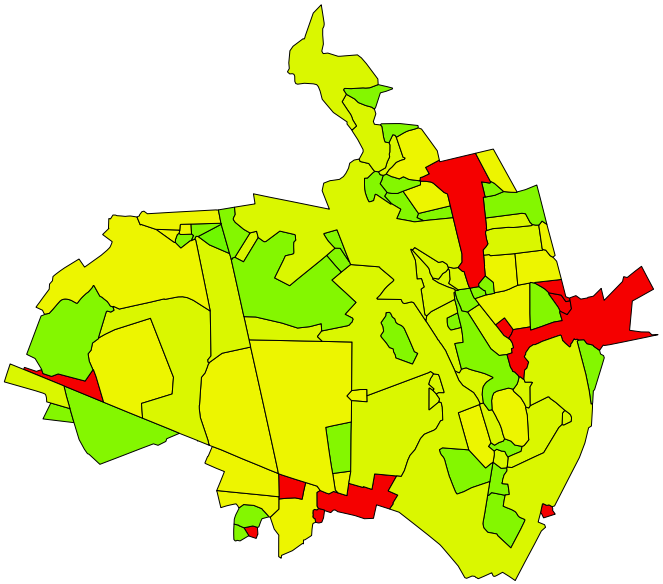

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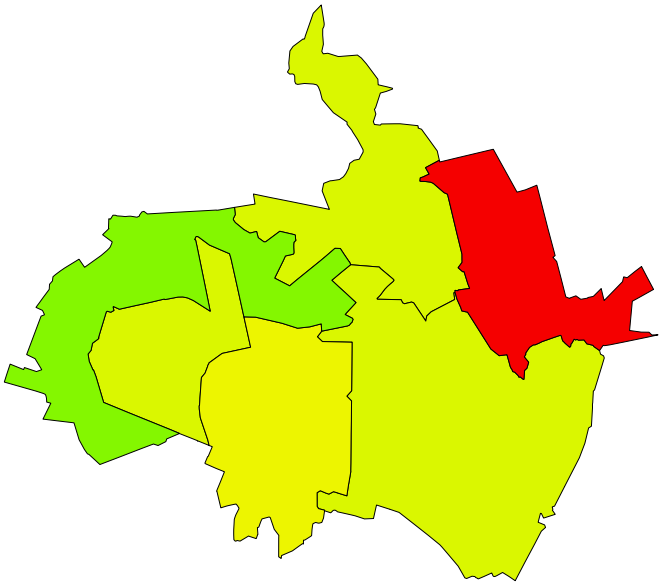

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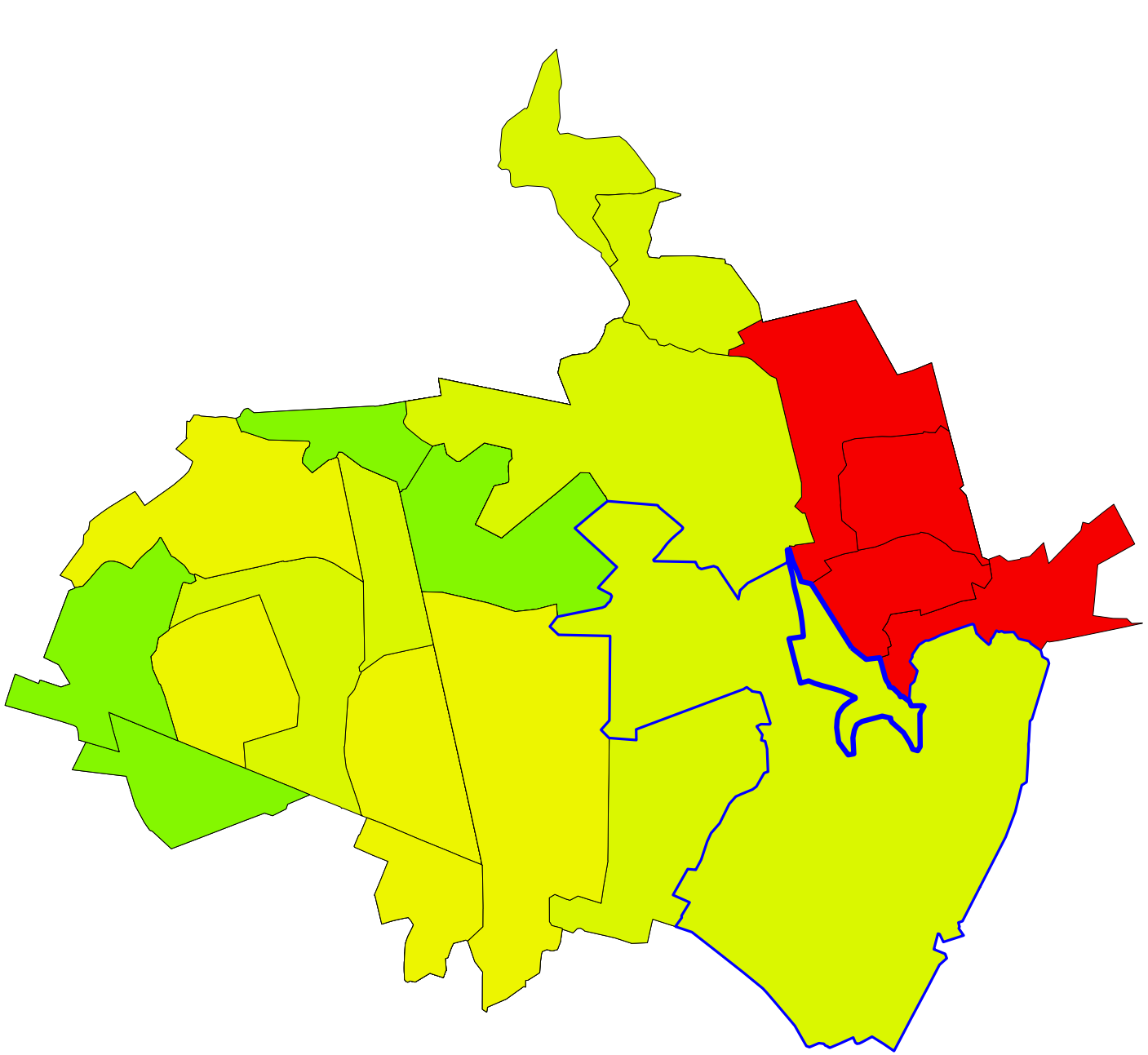

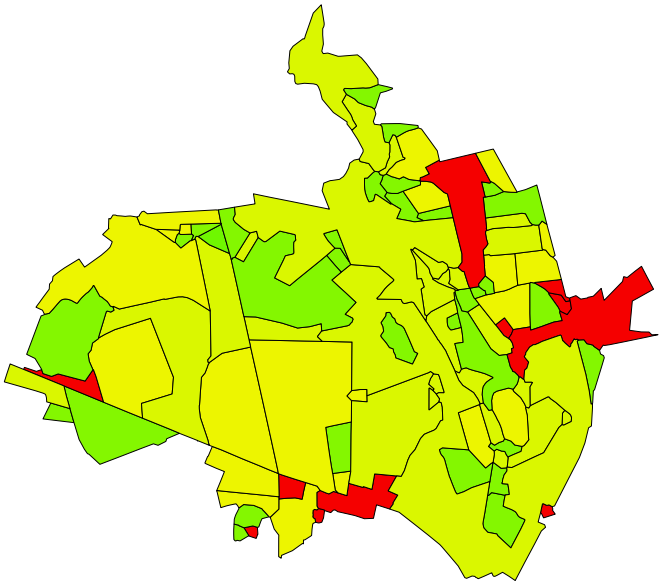

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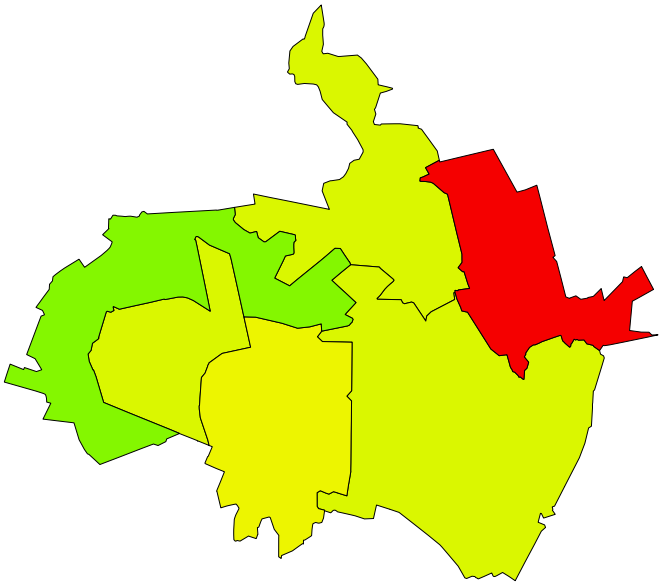

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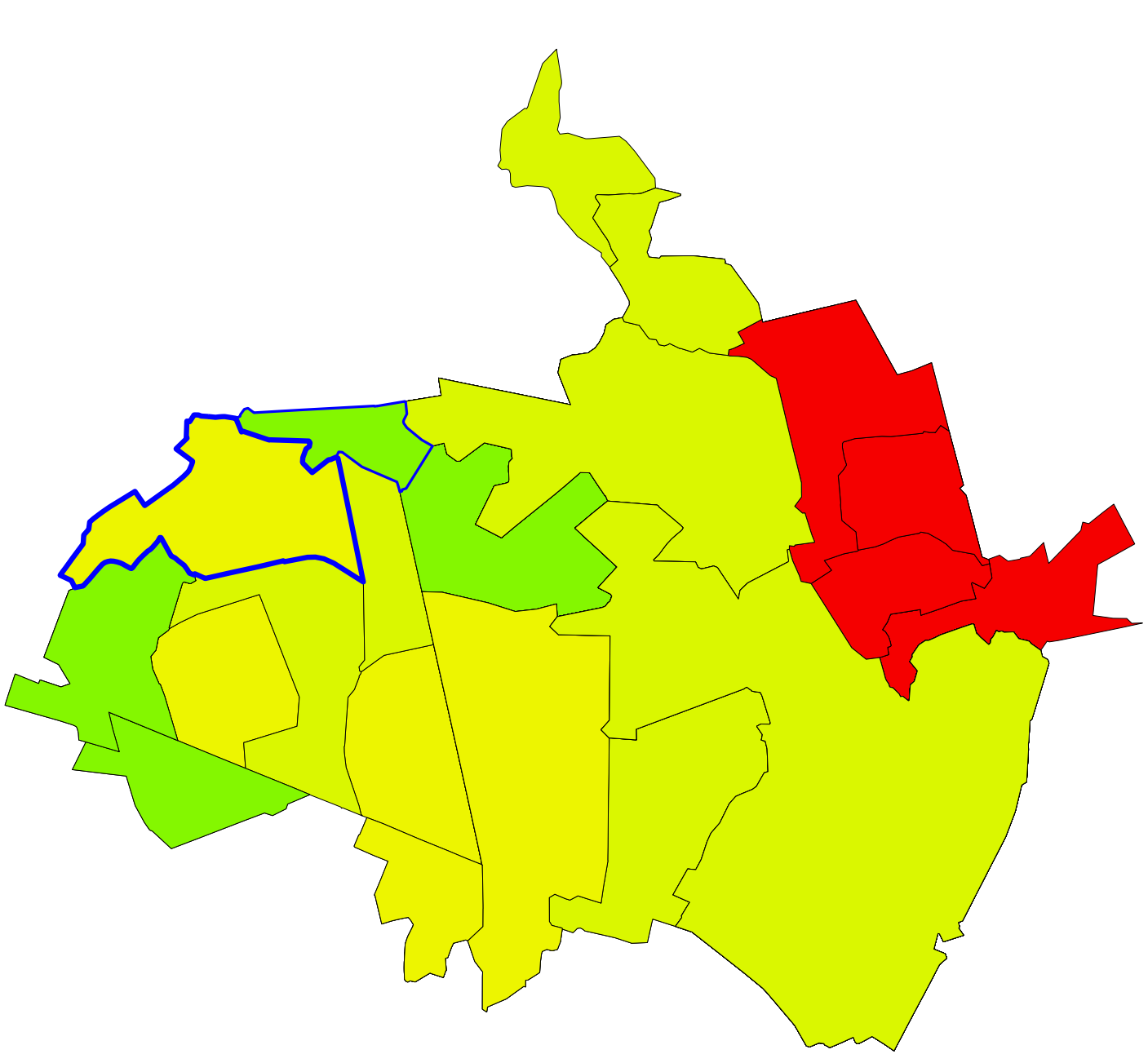

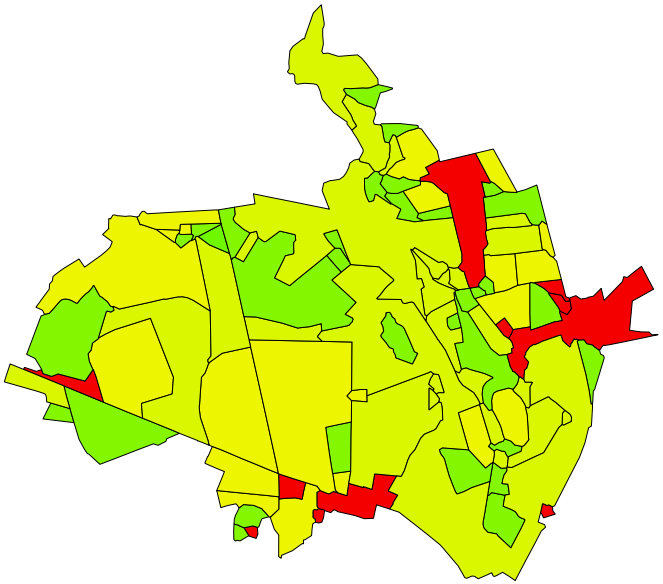

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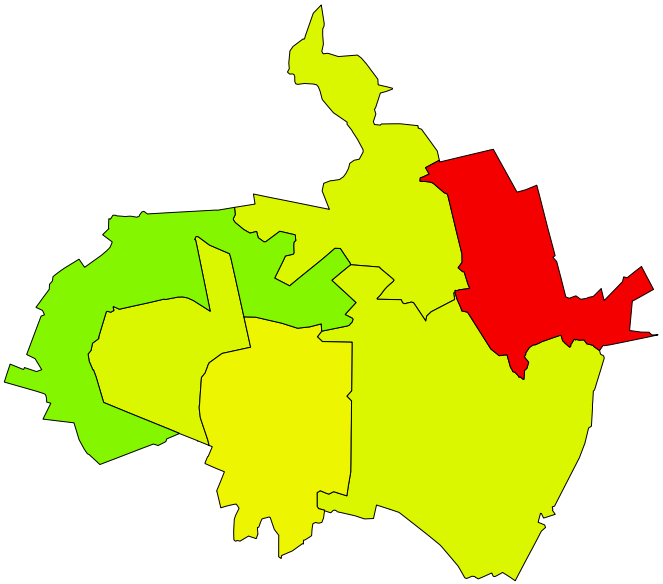

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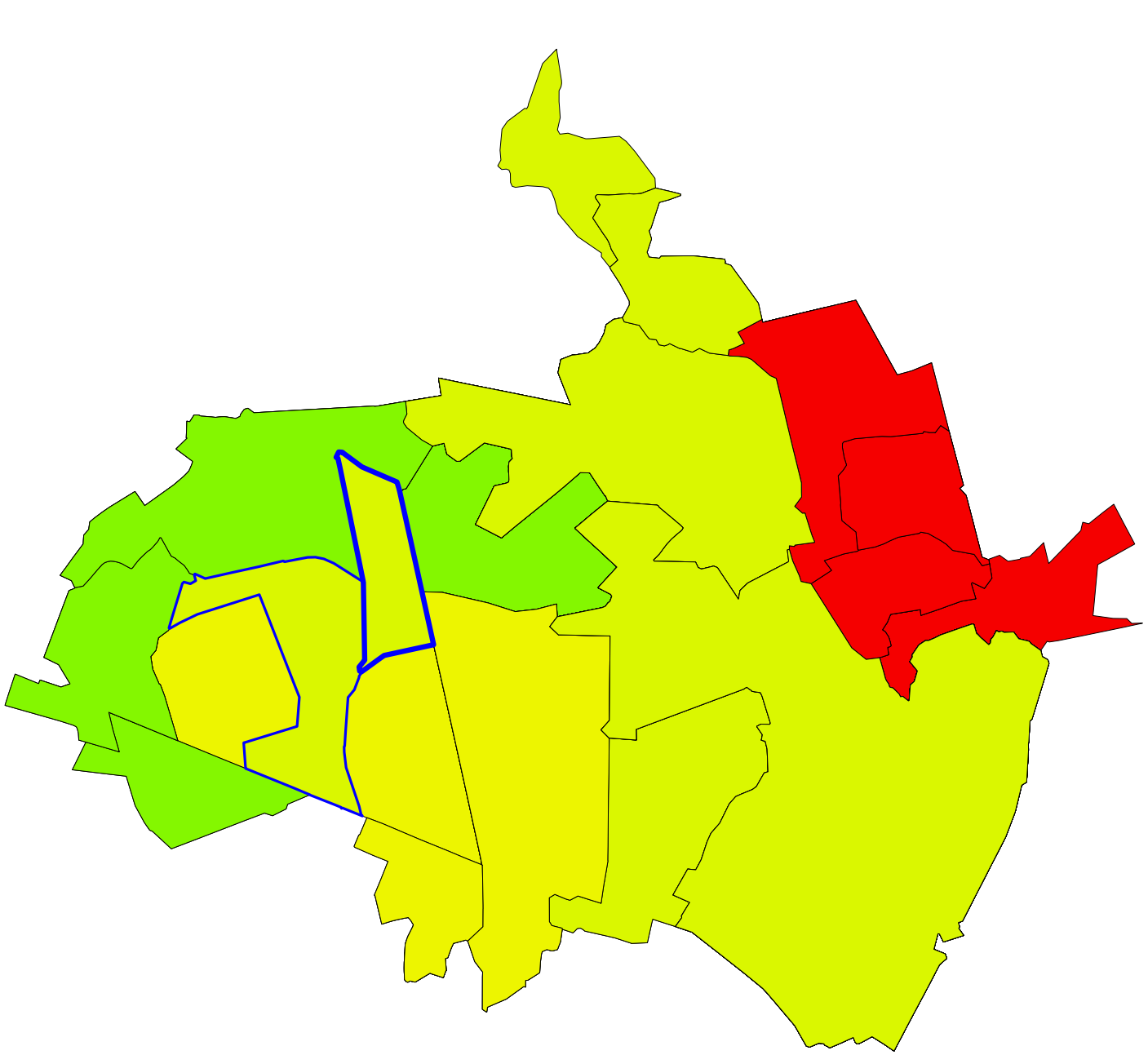

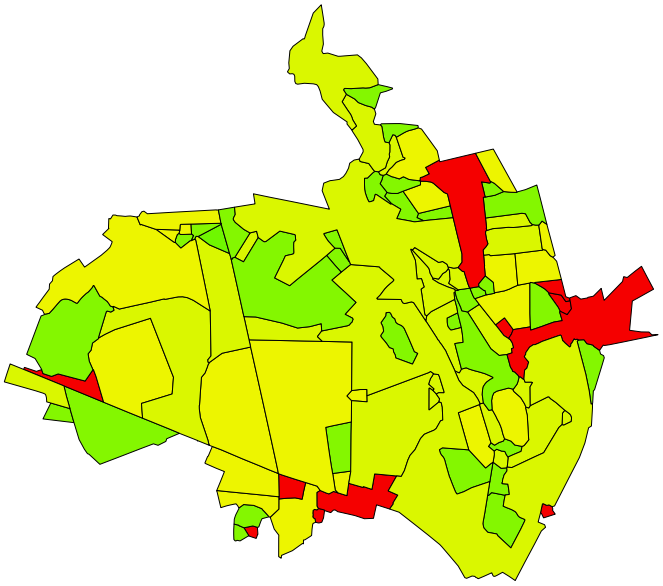

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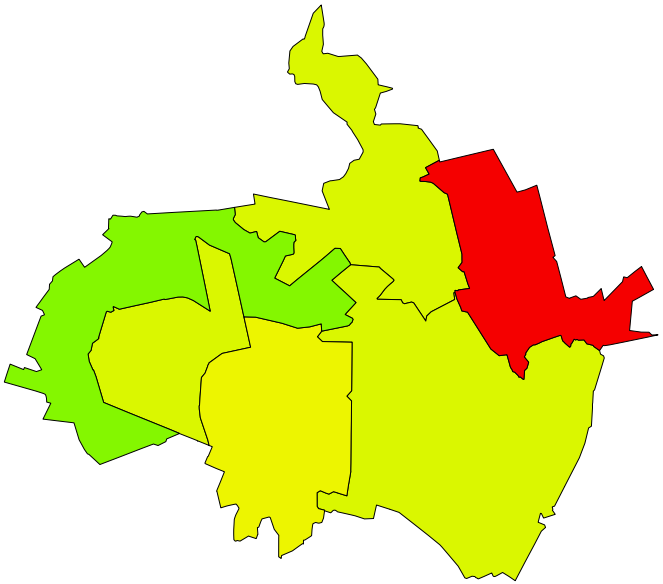

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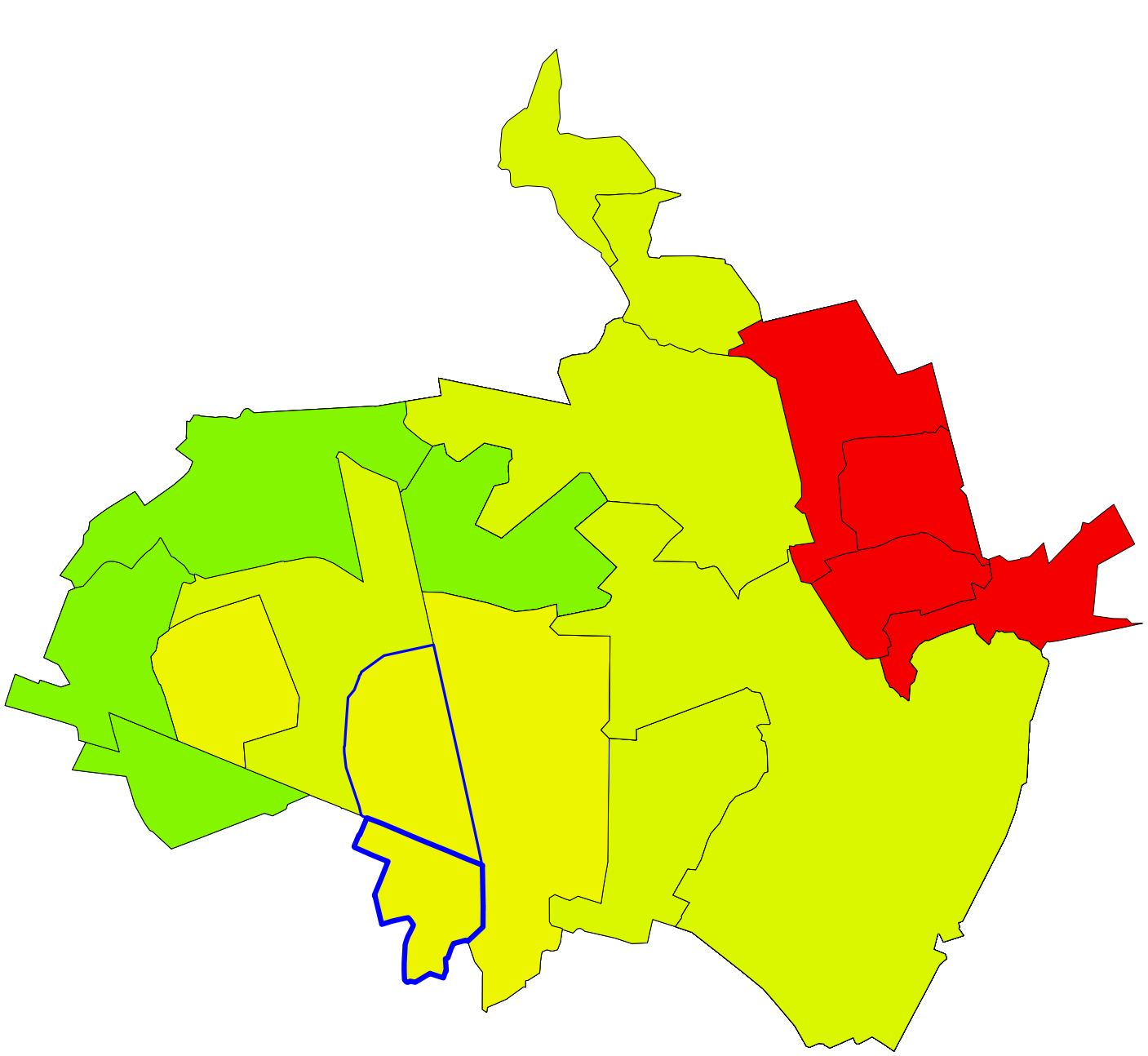

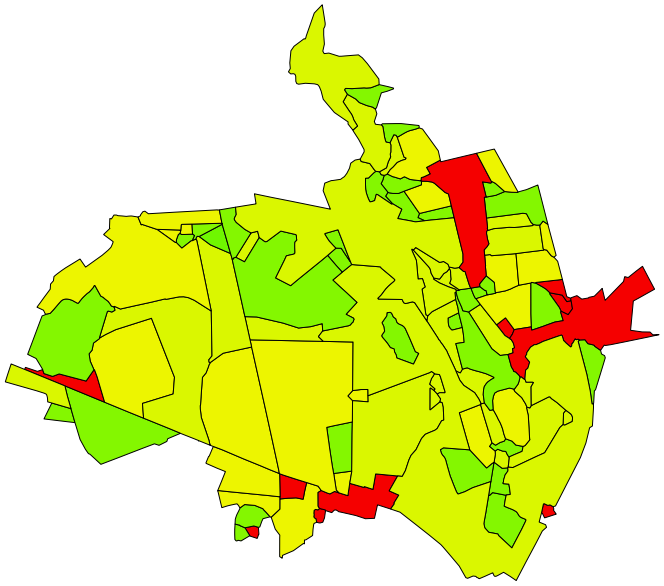

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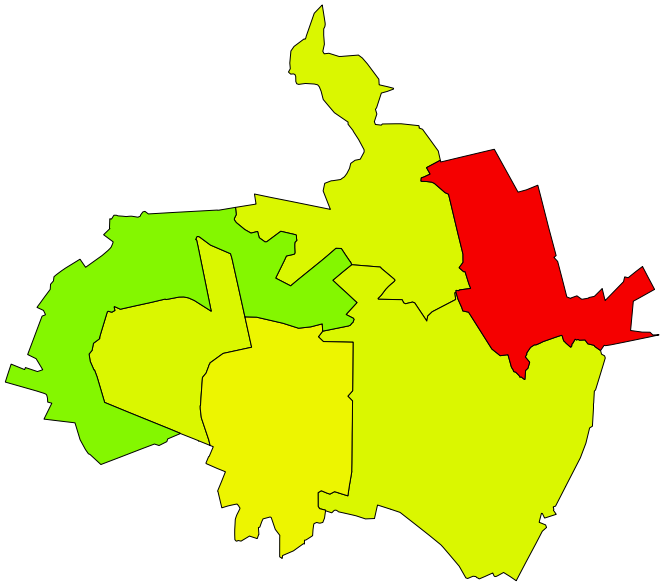

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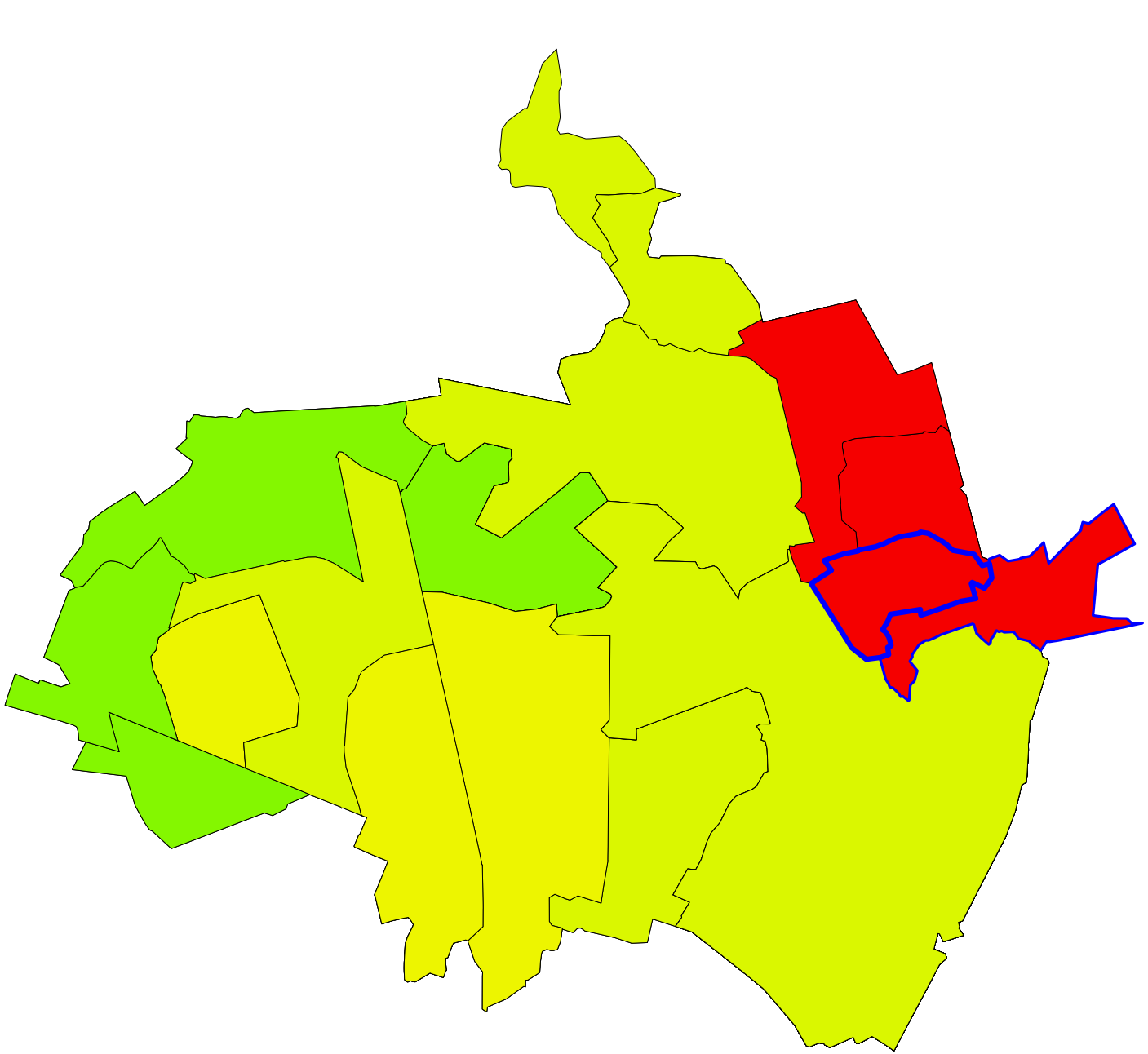

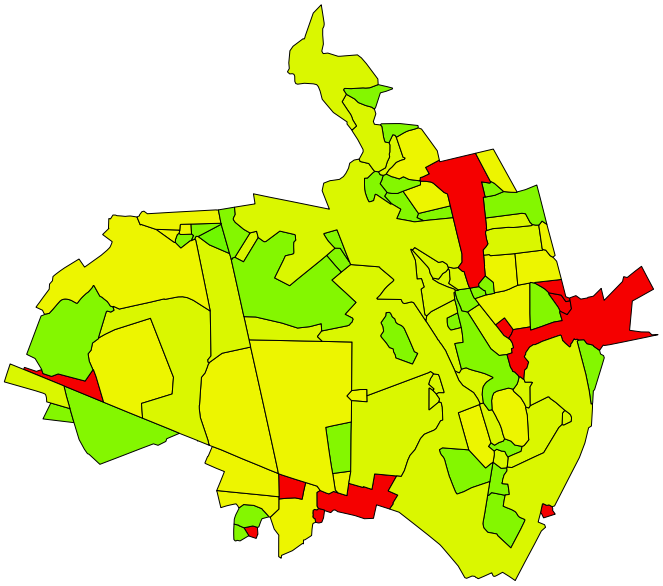

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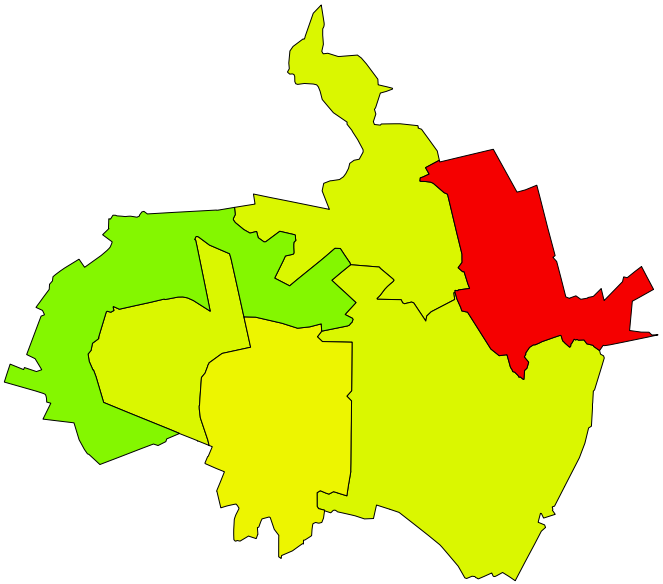

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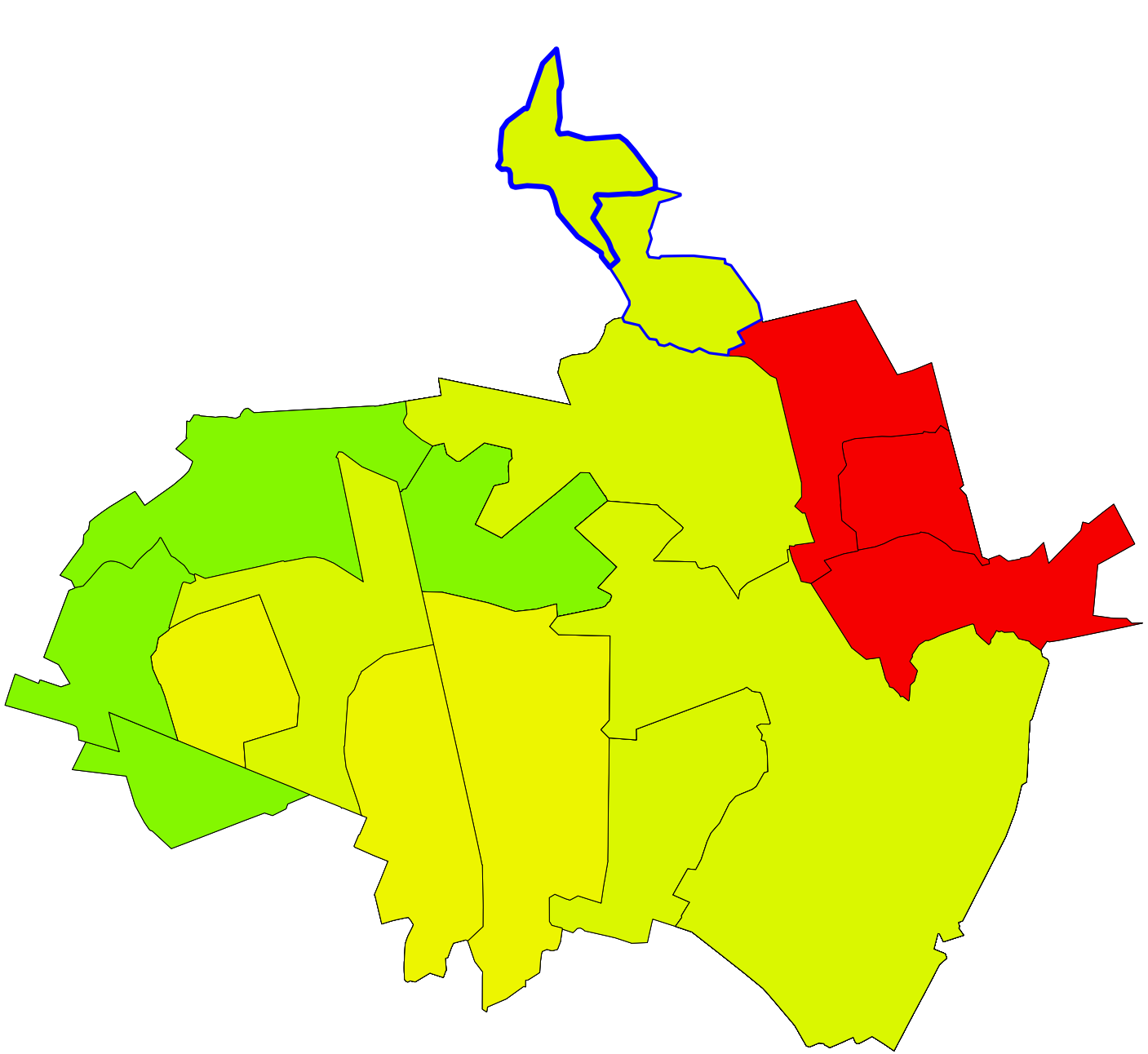

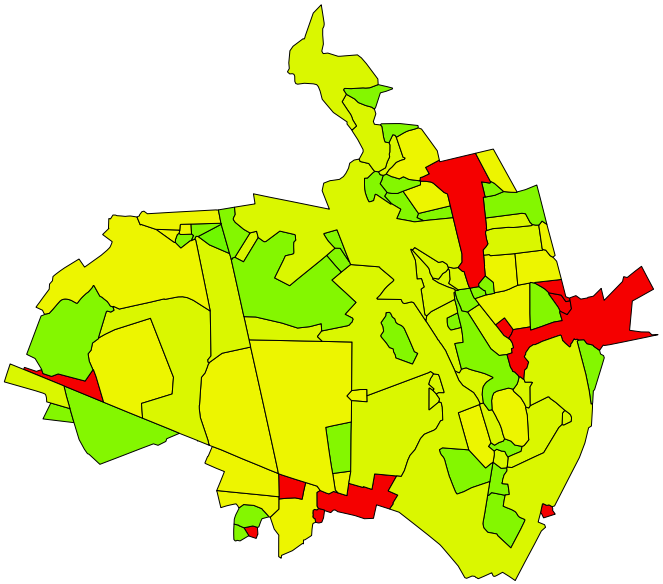

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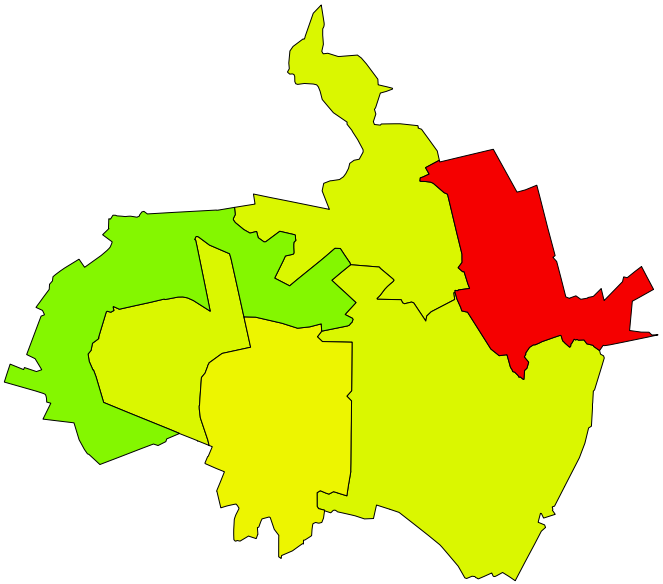

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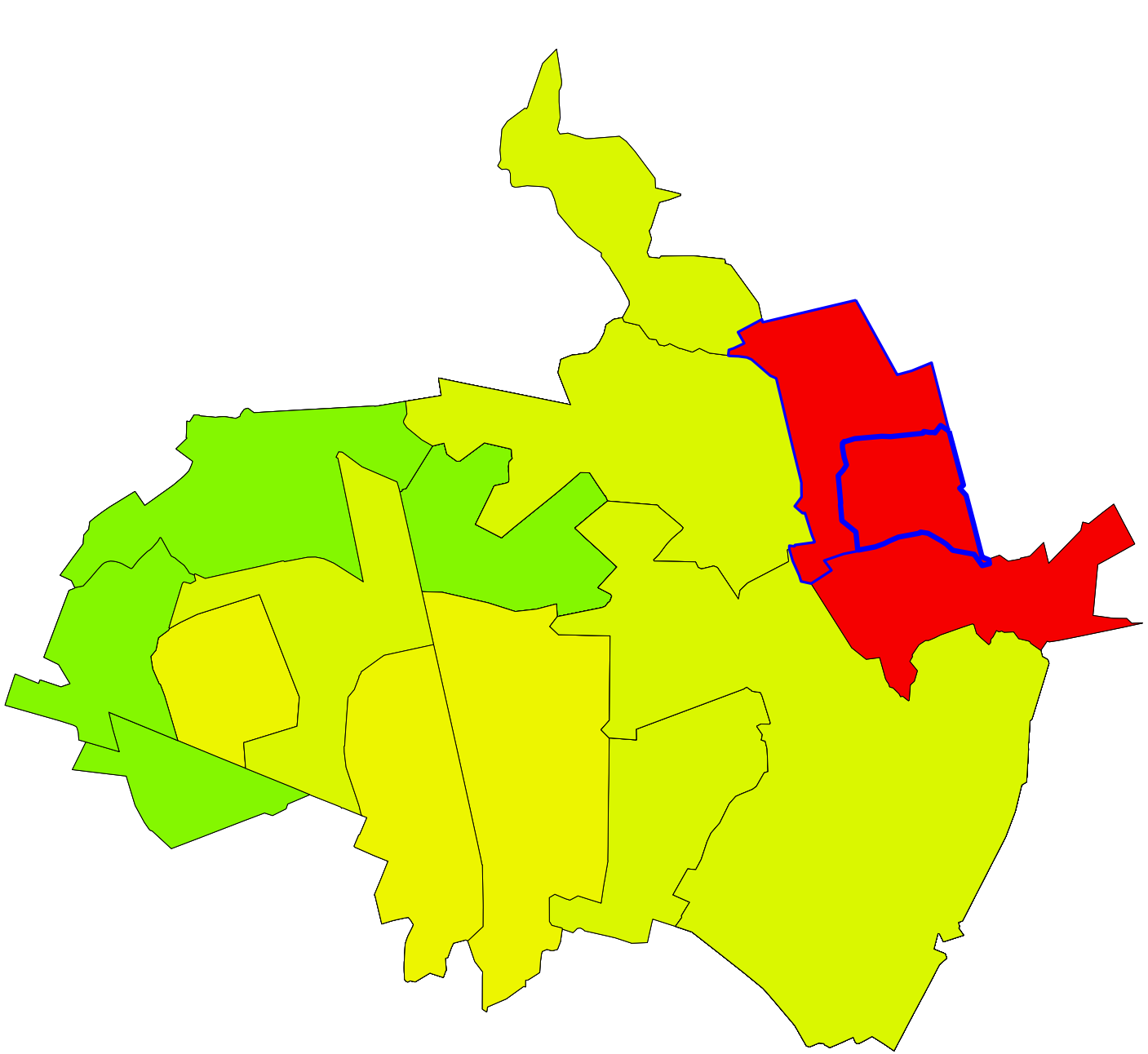

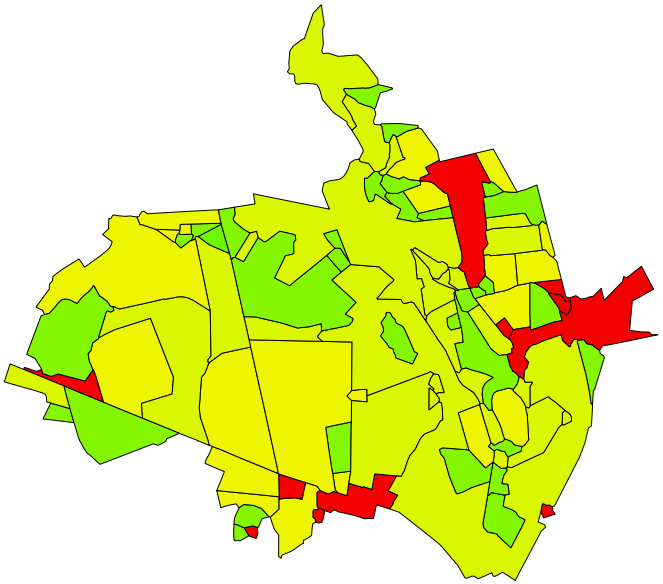

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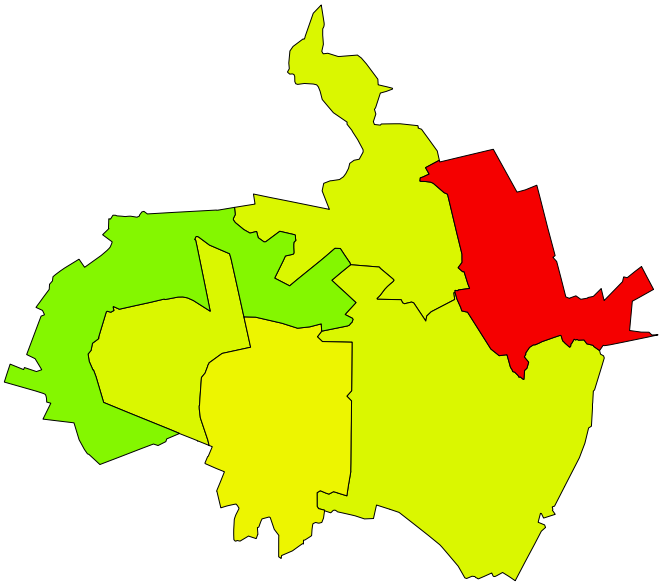

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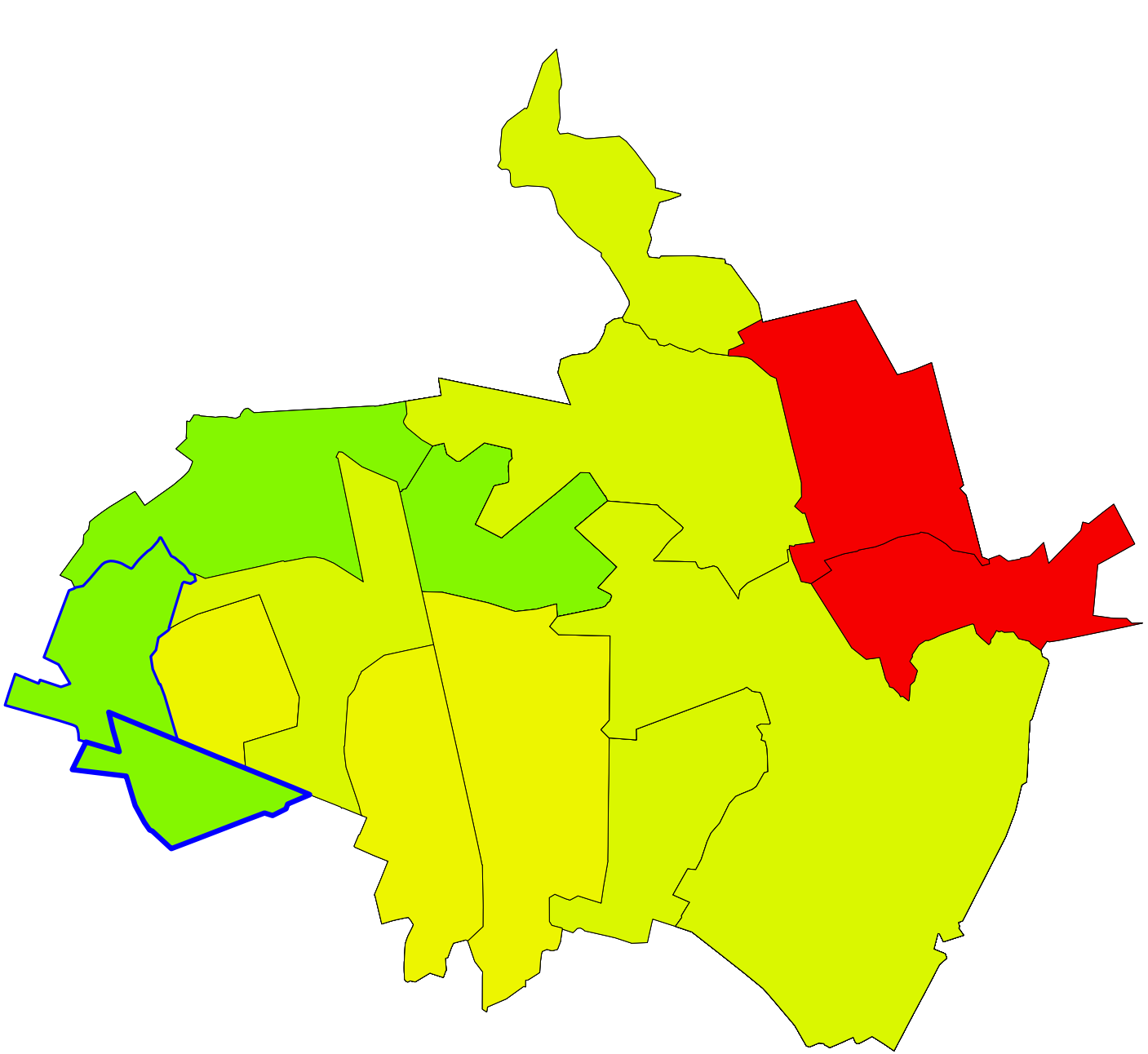

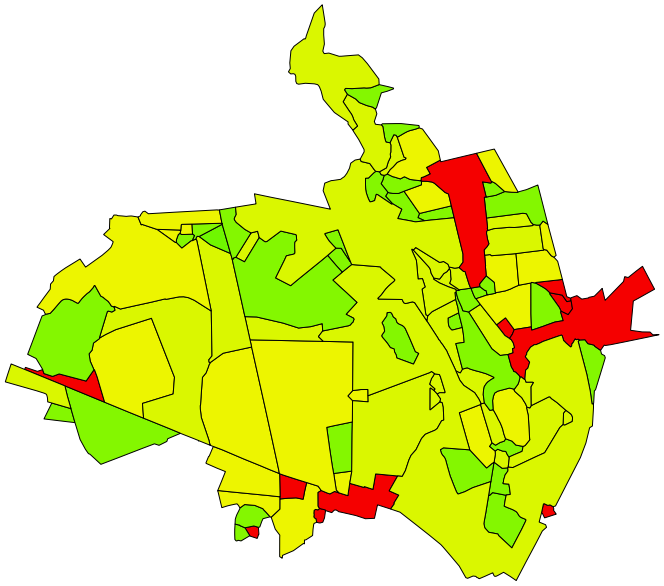

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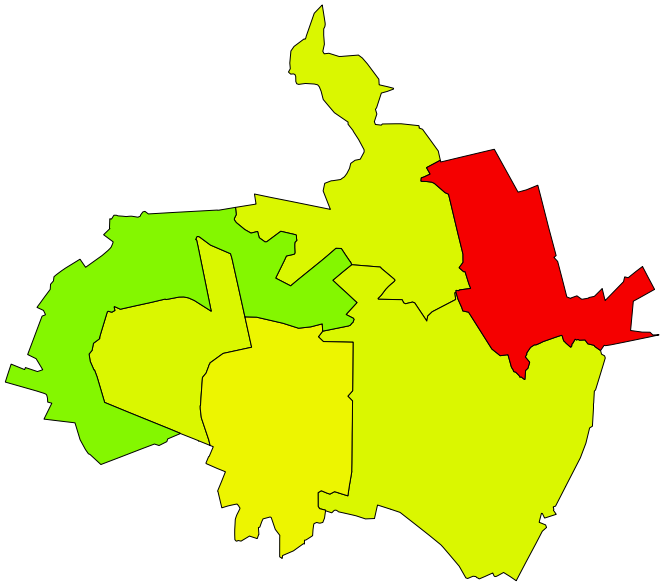

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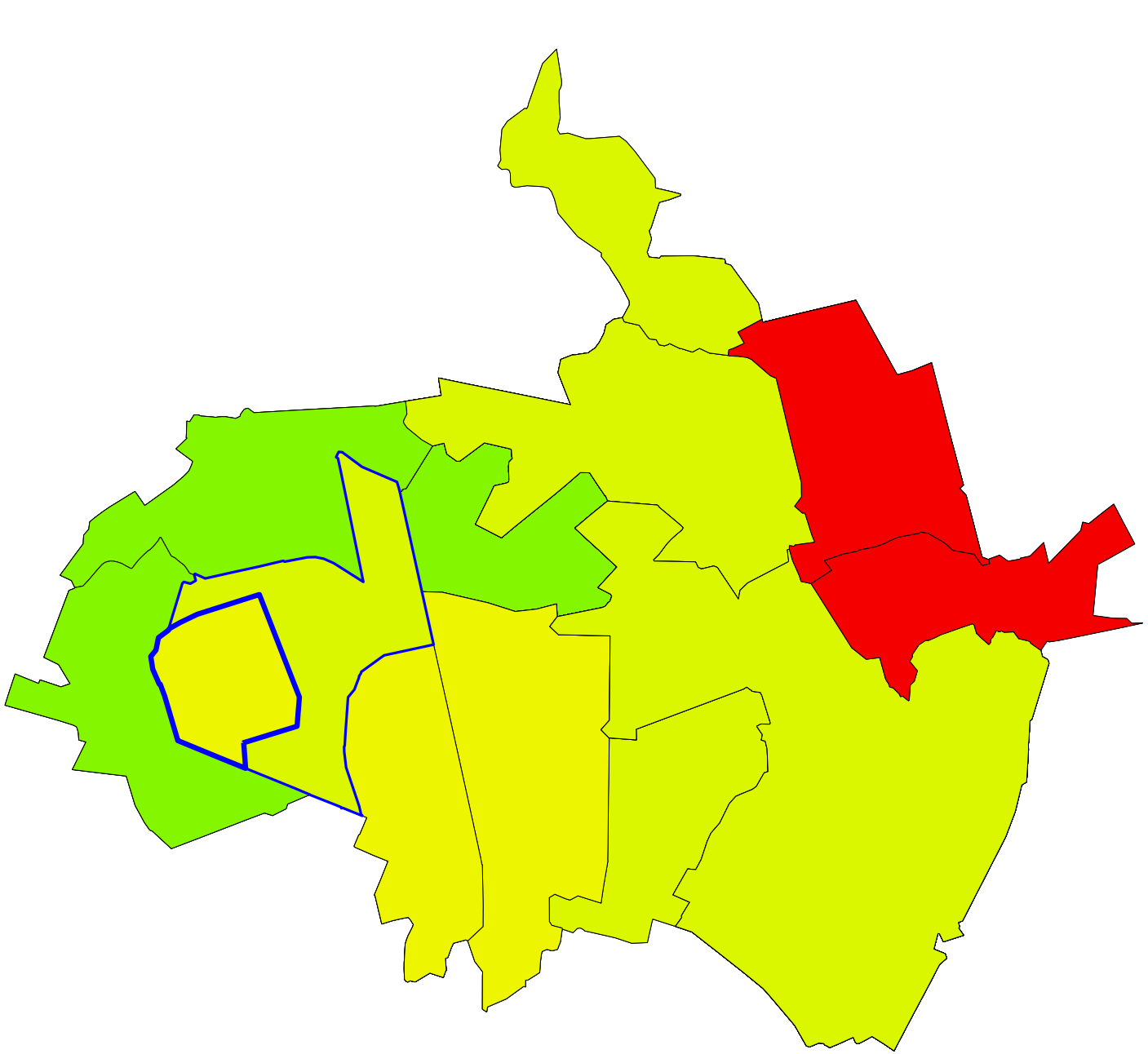

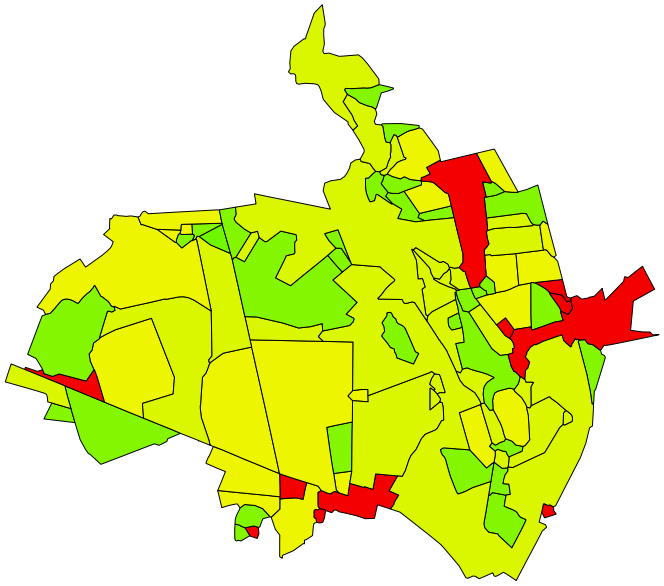

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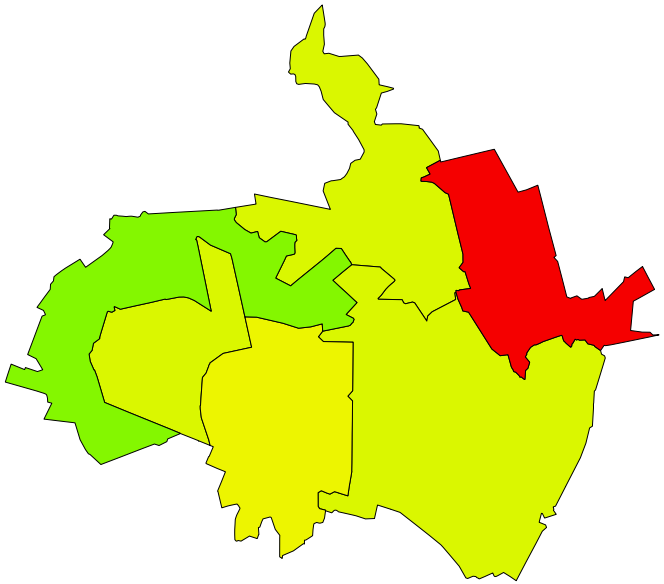

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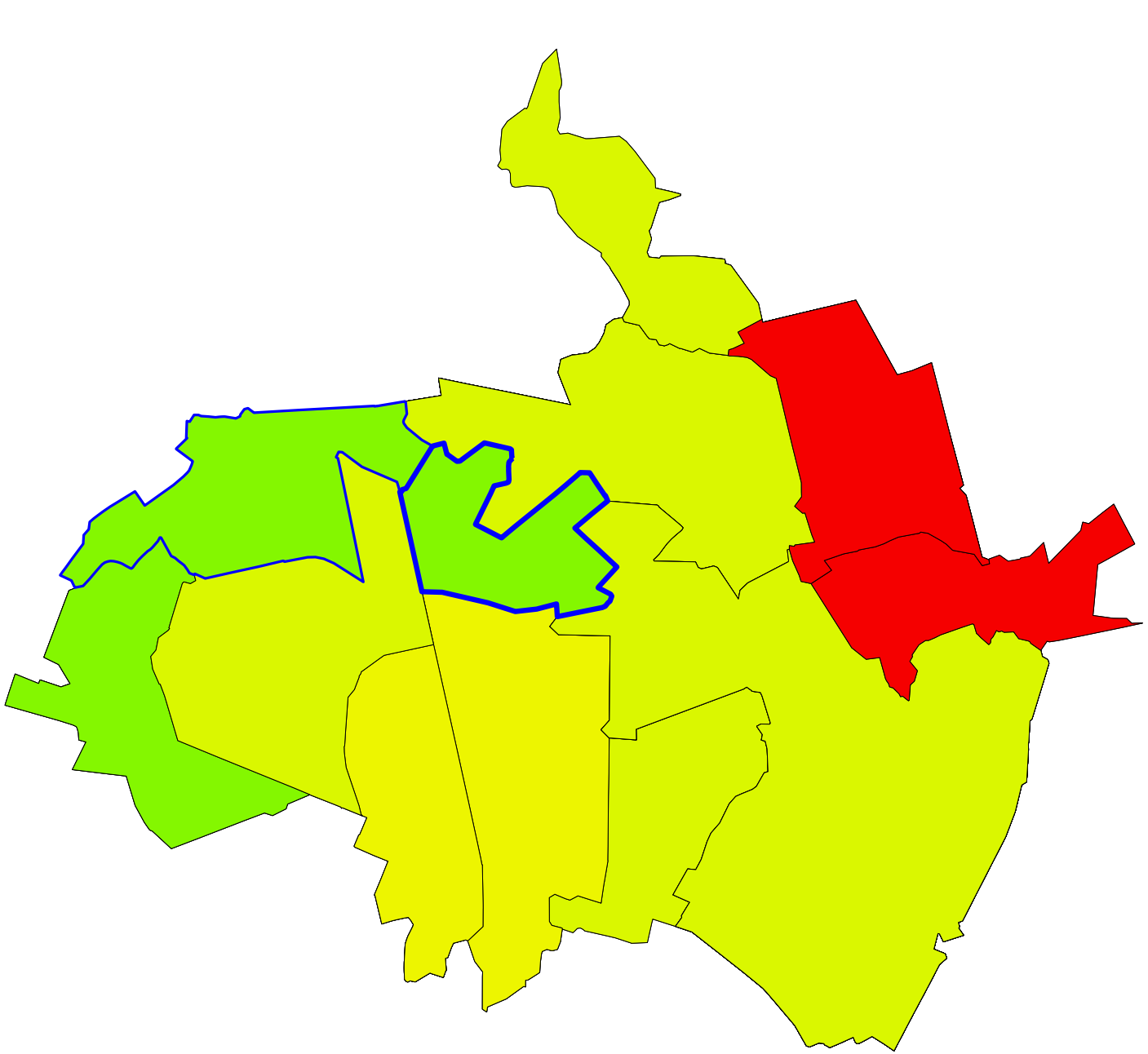

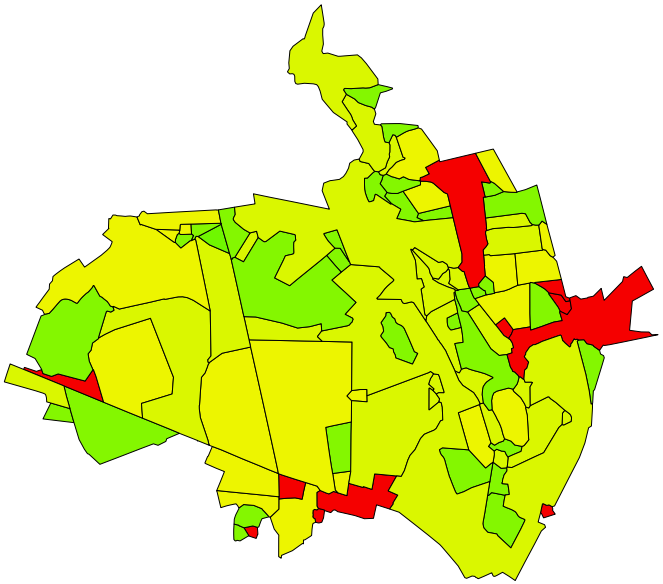

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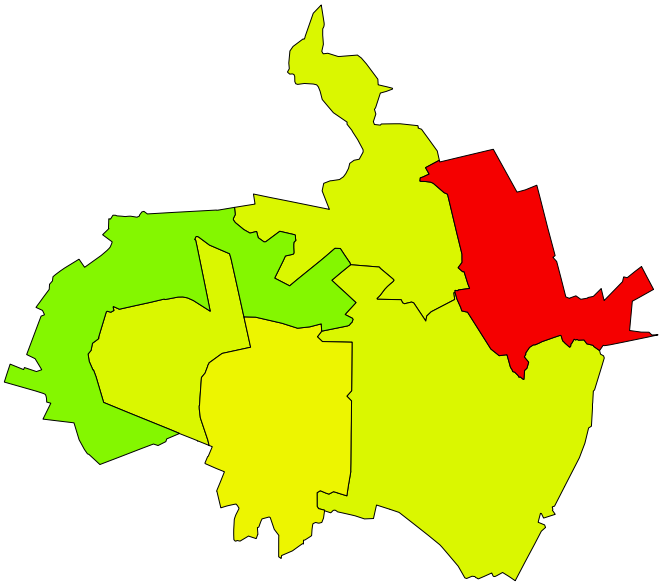

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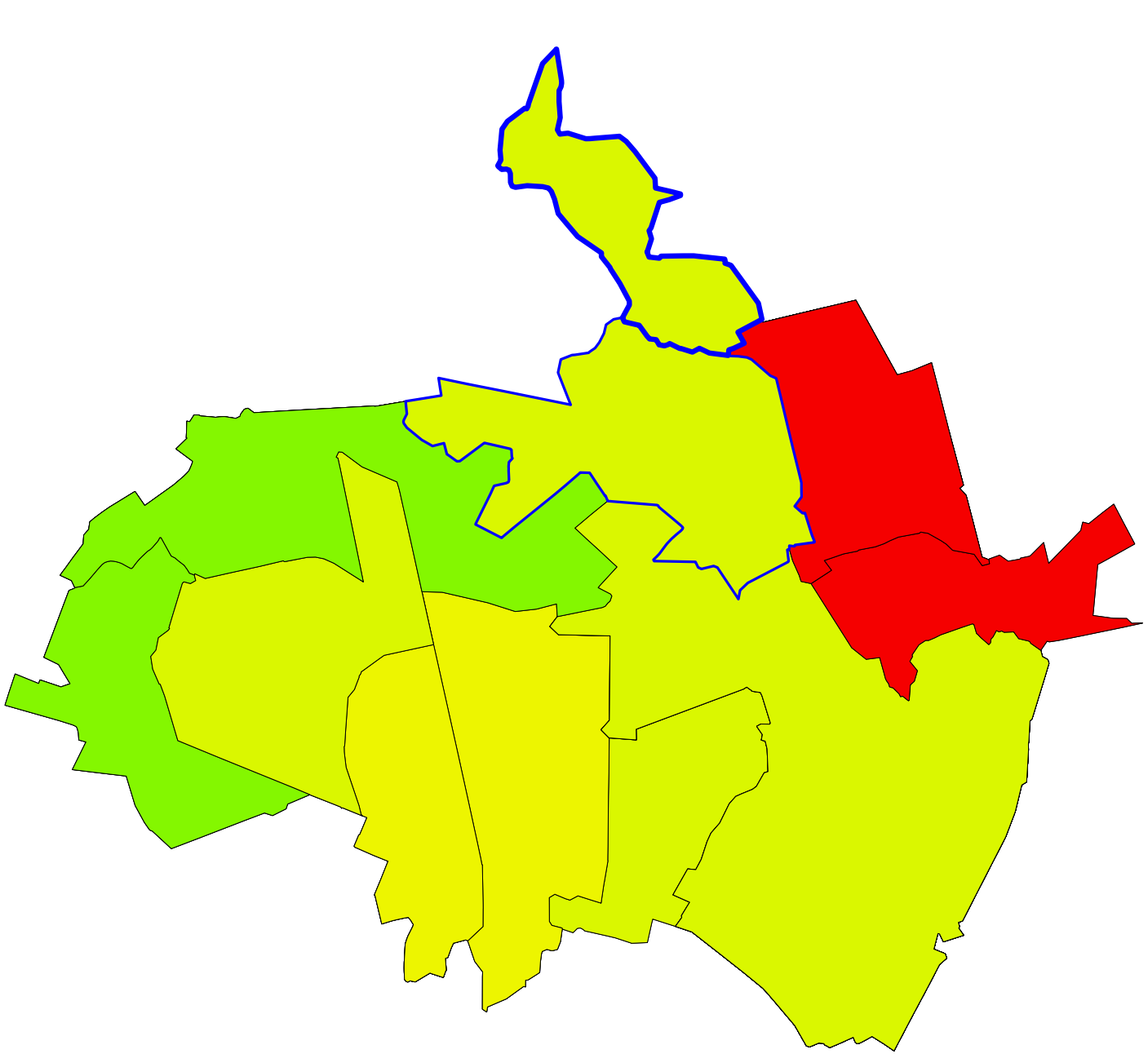

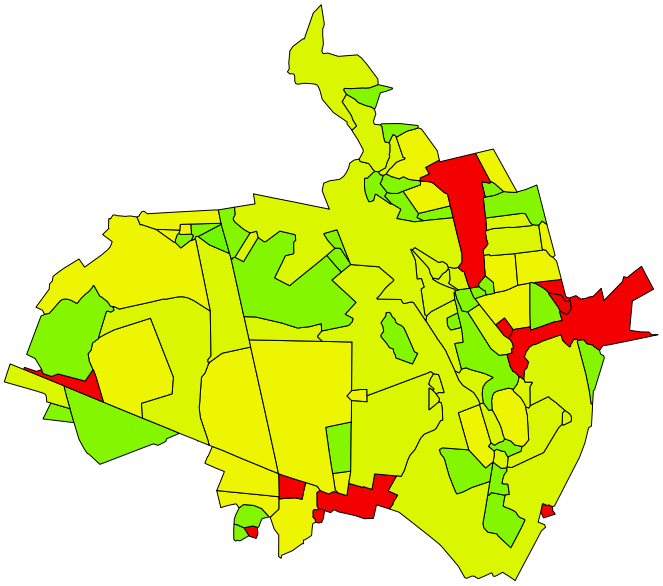

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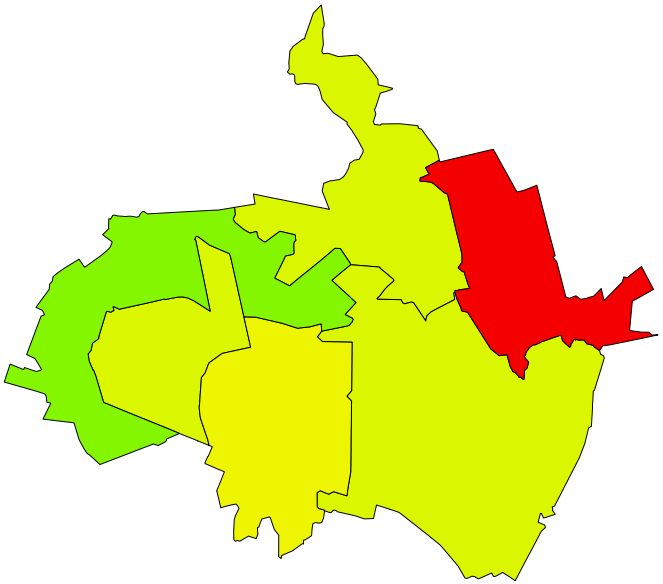

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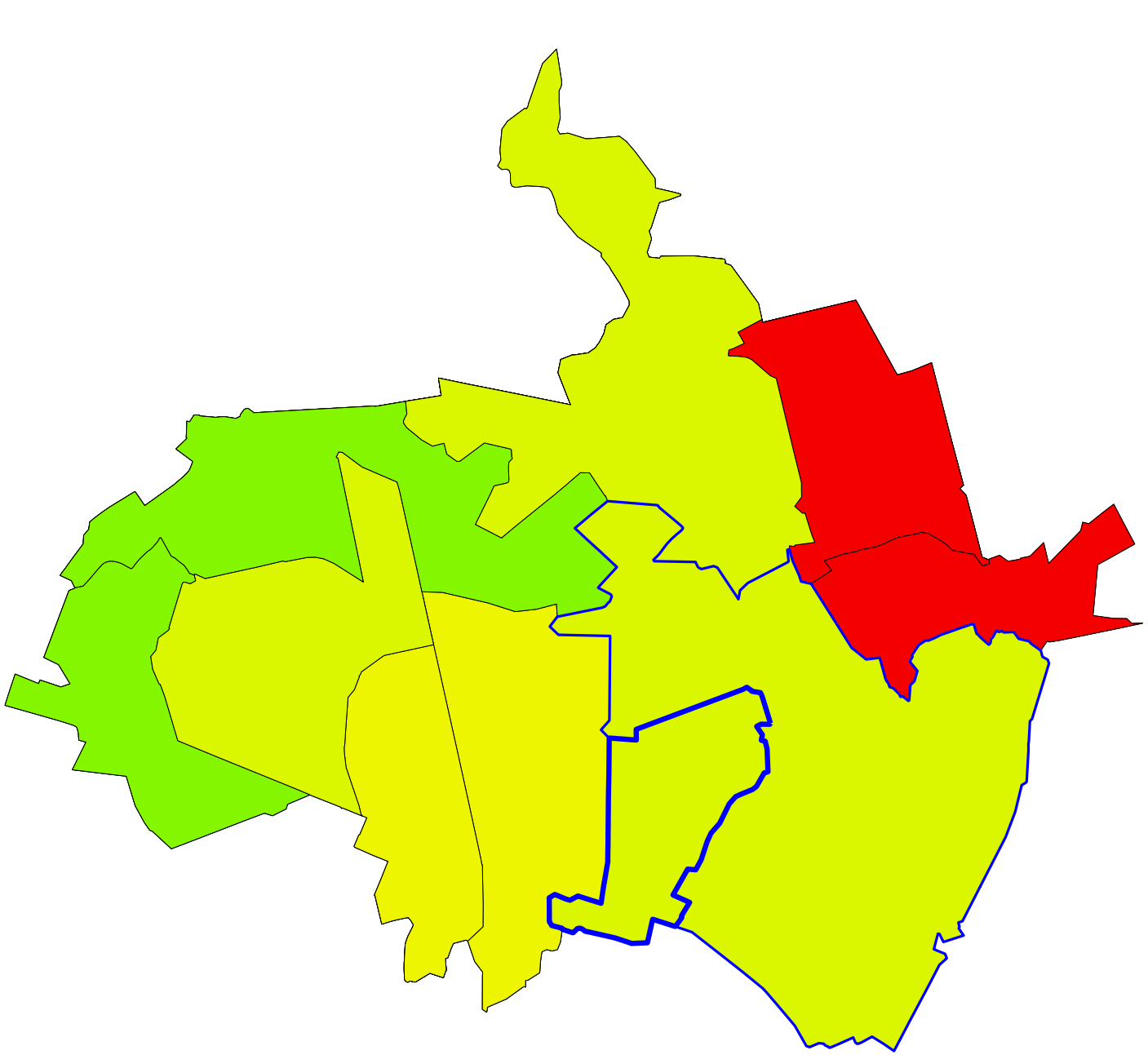
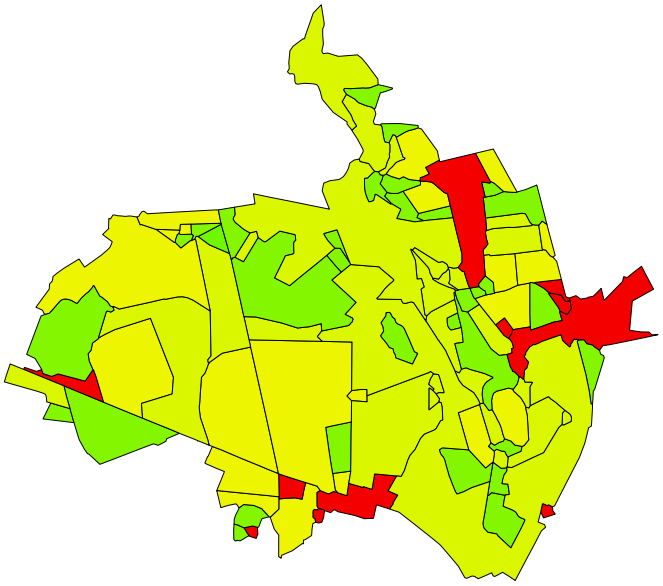
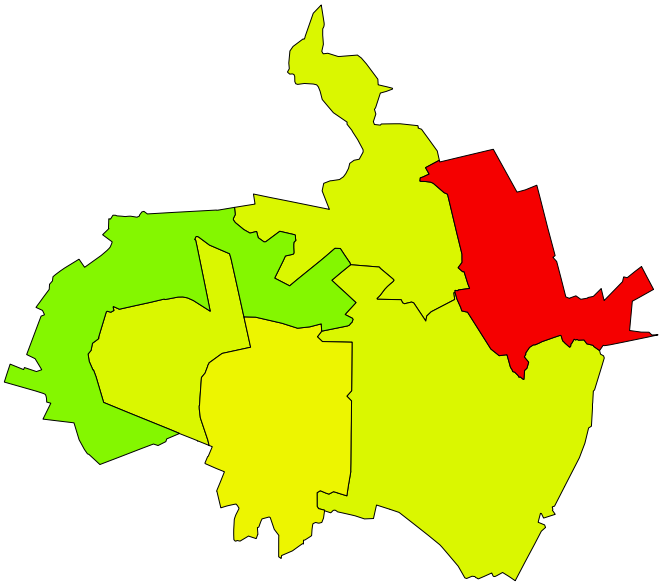




source: 92 patches



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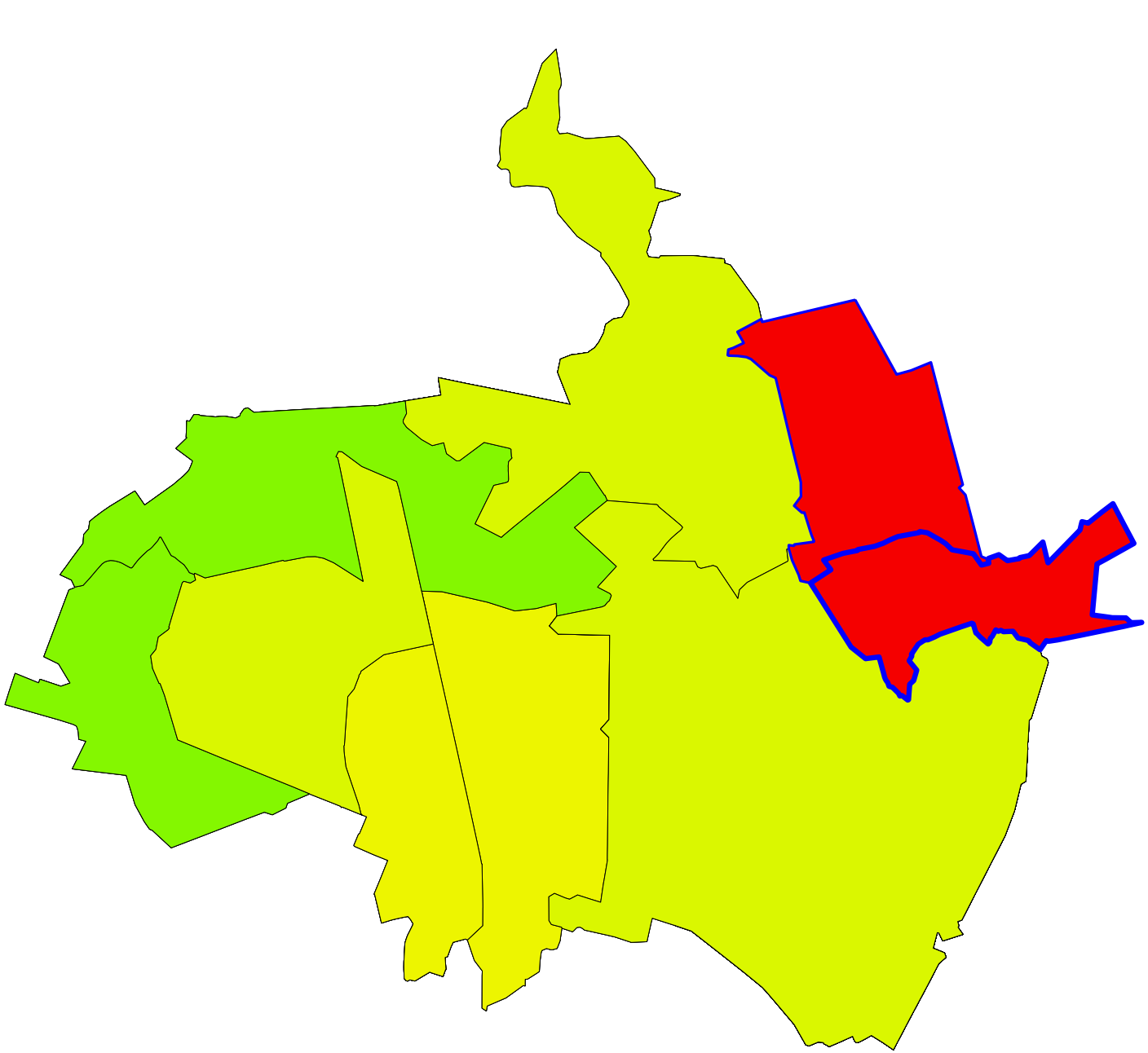

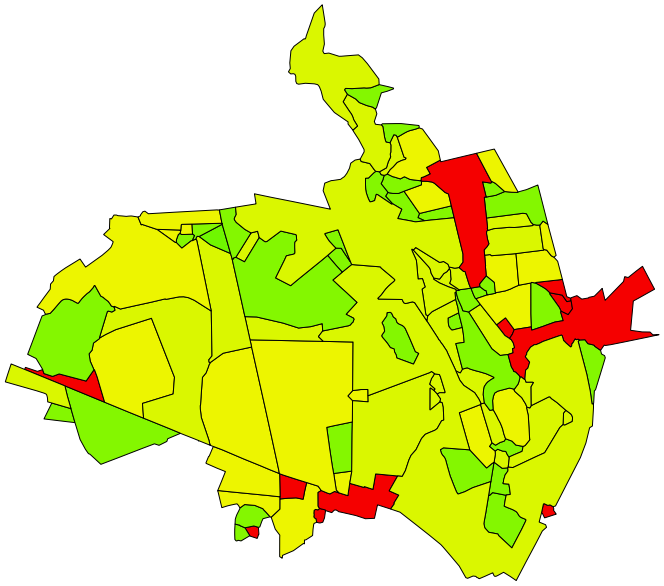

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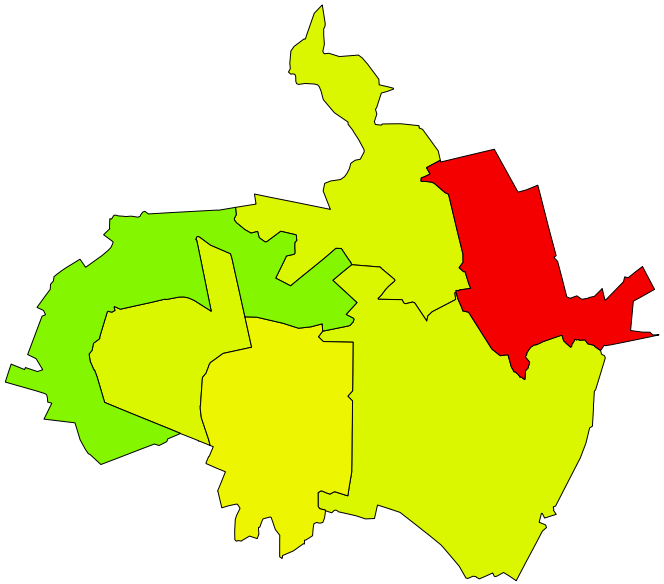

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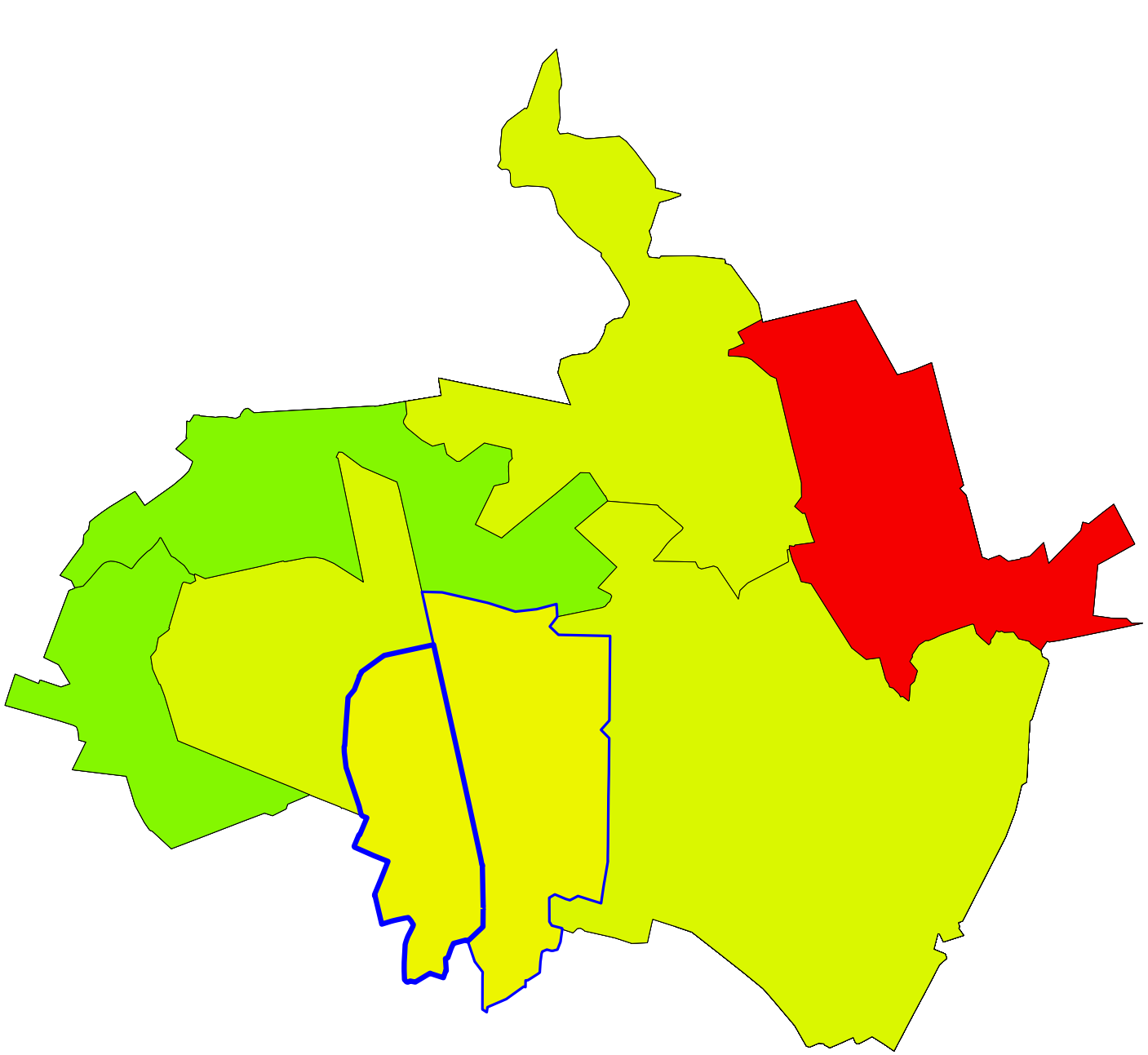

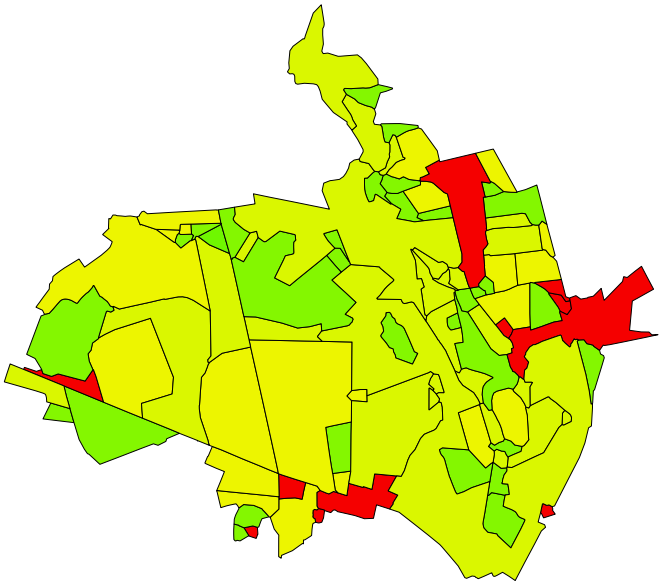

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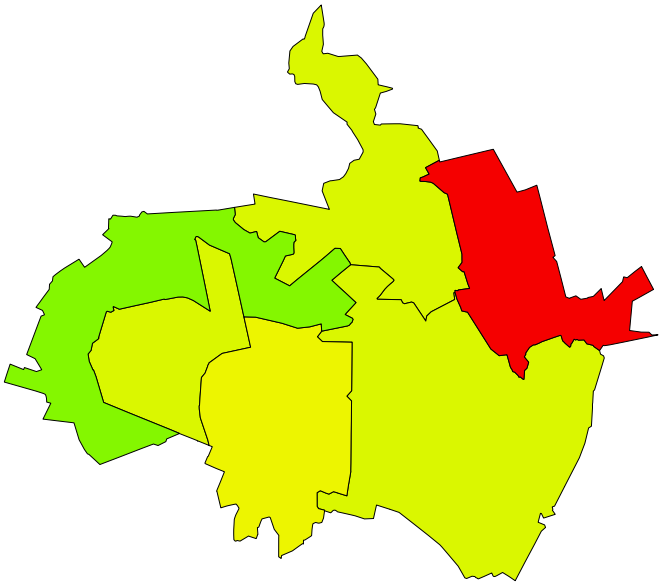

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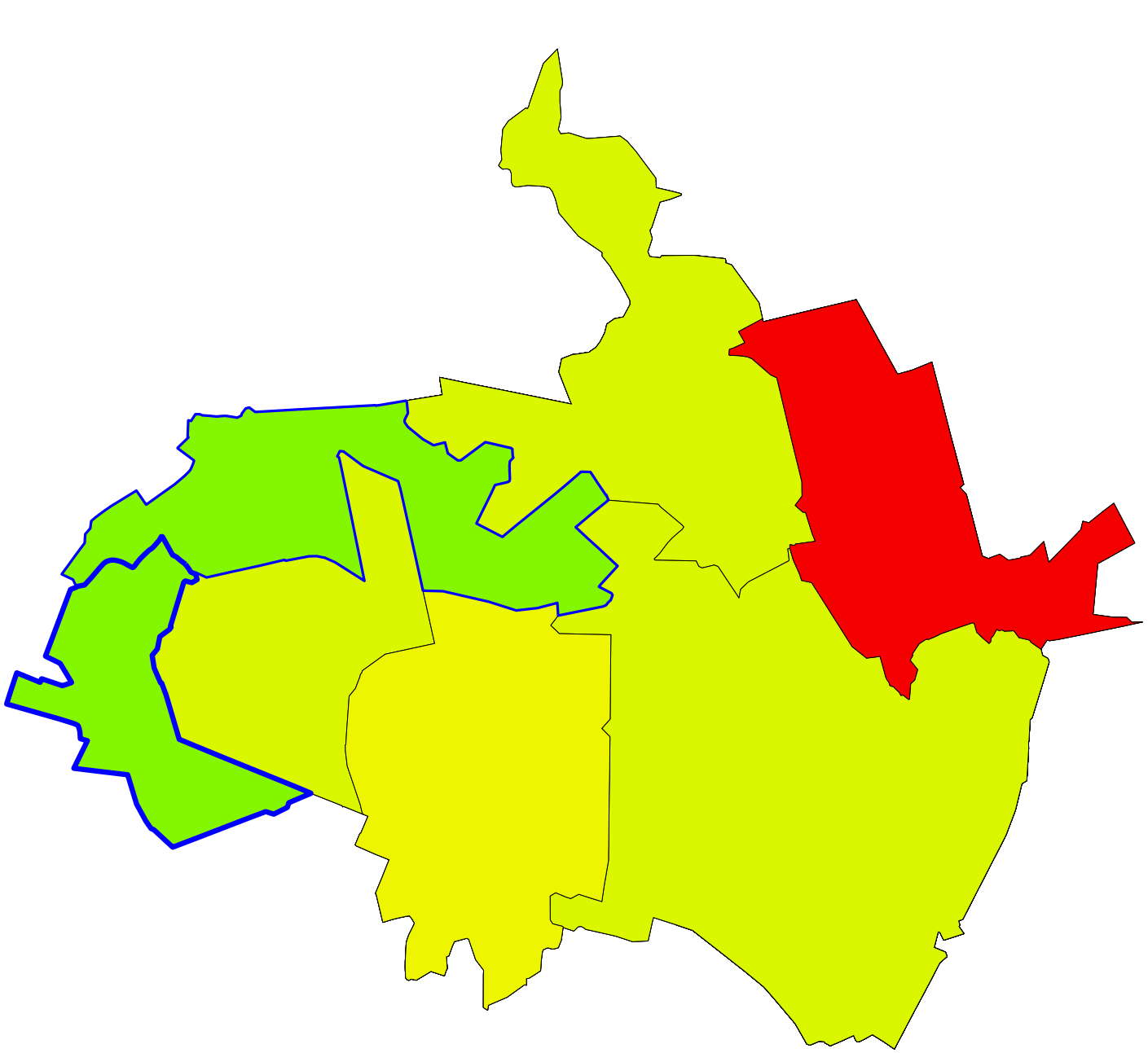

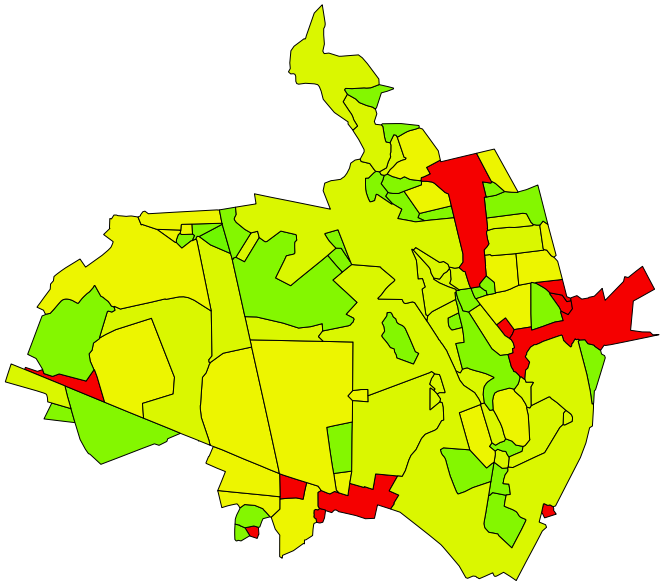

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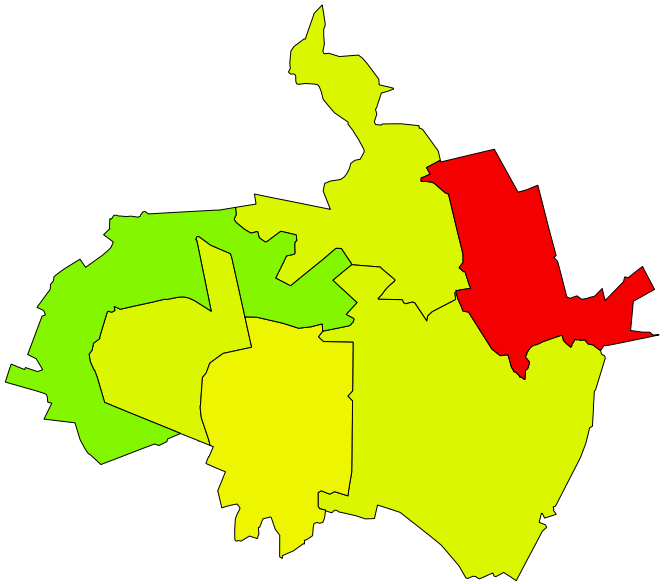

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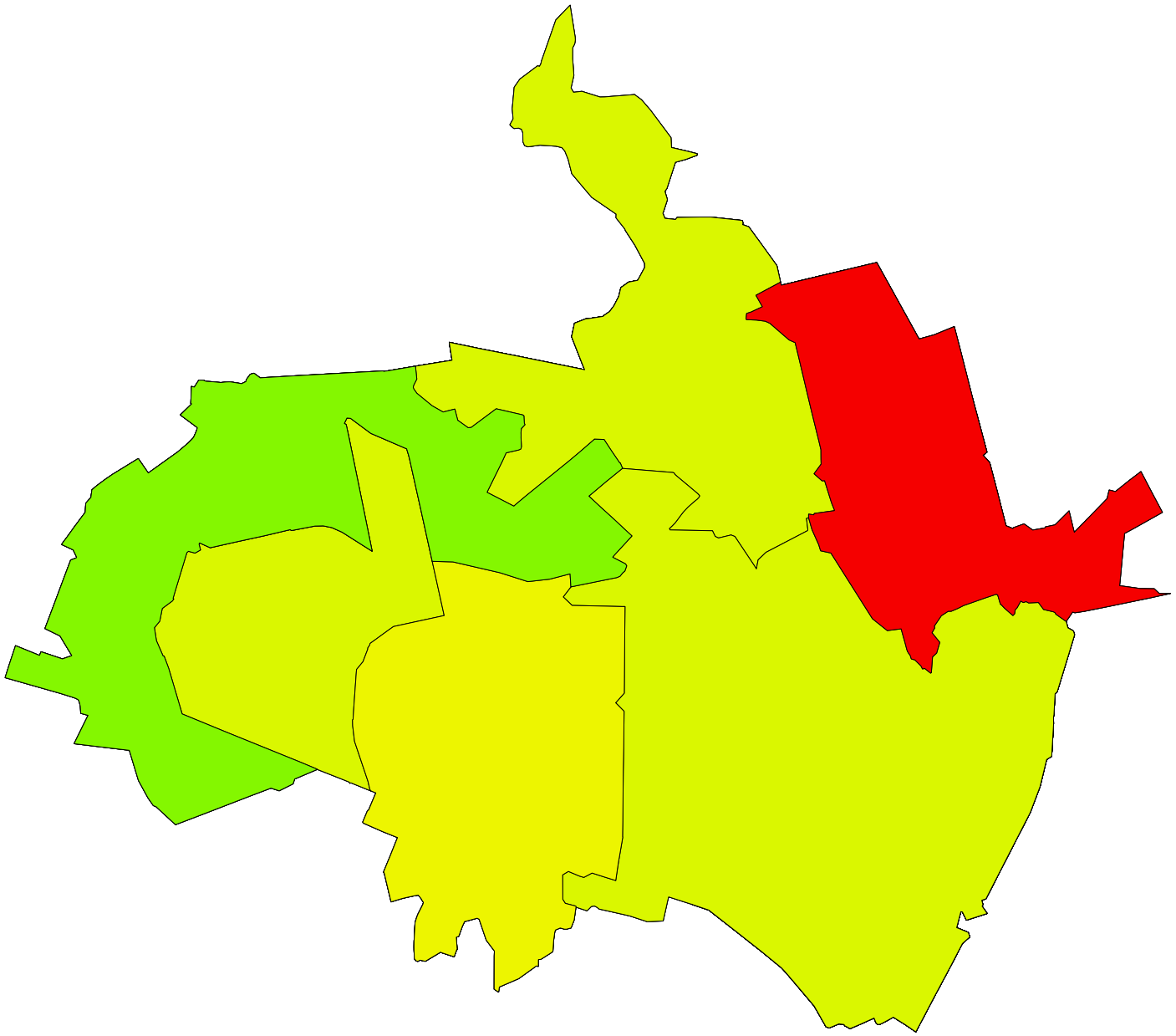

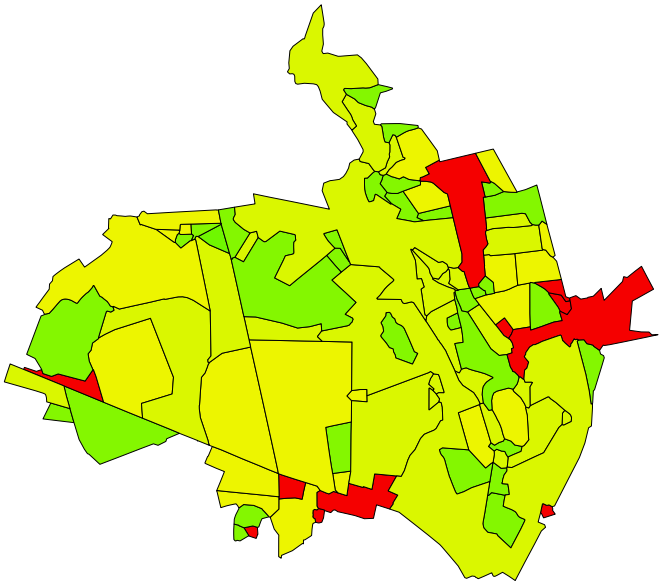

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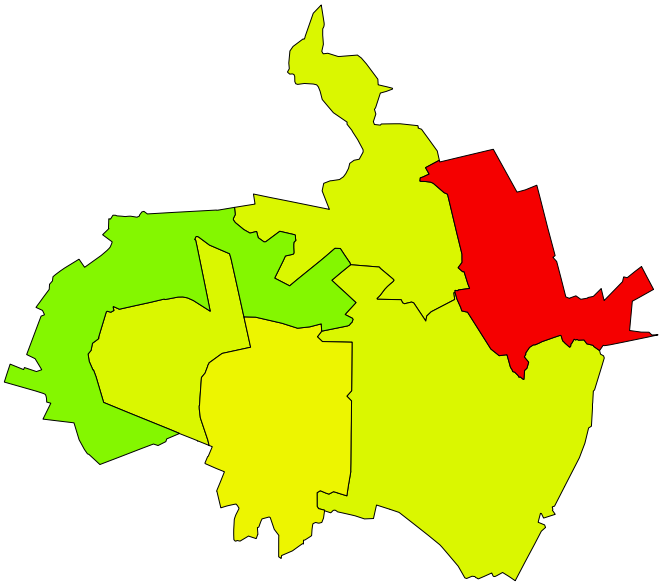

target: 6 patches

Outline

- Our Example Problem
- Methodology
- Case Study
- Concluding Remarks

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Thank you!