



Citizen Science Local Pilots – Lot 1 Northumbria

Summary Report

Brendon Wilkins

With Jonski Millar, Anna van Nostrand, Maiya Pina Dacier
and Lisa Westcott Wilkins

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Summary Report

Prepared on behalf of:
Natural England, NCEA, DEFRA

Report by:
Brendon Wilkins

With contributions from:
Jonski Millar, Anna van Nostrand, Maiya Pina Dacier and Lisa Westcott Wilkins

DigVentures

5 Witham Studios
Hall Street
Barnard Castle
County Durham
DL12 8JB

hello@digventures.com
0333 011 3990



Purpose of document

This document has been prepared as a technical report to detailing the results and findings of the Citizen Science Local Pilots – Lot 1, Northumbria project, undertaken by DigVentures, on behalf of Natural England. Deep Time is a multi-year project investigating whether Collective Intelligence can enable mass engagement with Earth Observation Data (EO), empowering citizens to map natural and cultural heritage in advance of largescale landscape transformation.

The purpose of this document is to provide a comprehensive account of the project results and citizen science methodology undertaken between October 2023 and March 2025. DigVentures accepts no responsibility or liability for any use that is made of this document other than by the Client for the purposes for which it was originally commissioned and prepared.

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Project summary

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Jacqueline Finn, Lara Fiorani, Sophie Firmston, Beth Fisher, Joe Fitzpatrick, Anne Fitzpatrick, Karen Flanagan, John Fletcher, George Fordham, Aly Foreman, Debbie Forster, Emily Foster, Kate Foster, Kirsty Fox, Joan Fox, Alison Foyster, Lucy Francis, Steven Francis, Susan Melody Frank, Rosie Frankenberg, Nick Freeman, Mary Freitas, Rodrigo Fuentes, Teruhisa Fukano, Christopher Fuller, Murray Gafkjen, Derek Gale, Paul Gallagher, Kelly Gardiner, Lucy Garrard, Isaac Garrod, Shirin Garside, Juli Gauthier, Patrick Gavaghan, Sandie Geddes, Angela Gee, Steven Geldart, Jo Gennari, Andy Gentry, Kristina Georgieva, David Gernon, Jayne Gerrard, Susan Getchell, John Gibbs, Niki Gibson, Heidi Gilboy-Dodds, Andrew Giles, Rebecca Giles, Kay Gillespie, Lisa Gillespie, Stuart Gillies, Marie Gilsenan, Ester Gimenez Mojon, Jules Godwin, Maggie Gonzalez, Michelle Goodall, Stuart Goodhead, Peter Goodrich, Elie Gordon, Helen Gordon, Emma Gordon, Louise Gosling, Neil Gostick, Robbie Gottlieb, Joseph Gozito, Patrizia Gozito, Oliver Grafton, Susan Granados, B Grant, Maria Graves, Andy Gray, John Gray, Karen Gray, Keith Greenwell, Liz Greenwood, Steve Griffin, Sabine Grimmig, Meirion Grimshaw, Katharina Gudelj Ensor, David Guerin, Olivia Guest, Cynthia Guy, David Gwilliam, G H, Liz Hadley, Helen Hague, Dawn Haida, Douglas Hall, Stephen Hall, Rob Hall, Gillian Hanlon, Chris Hanratty, Kevin Haran, Roman Harasymiuk, Sean Hardcastle, Alex Hardcastle, Paul Hardiman, Nicole Hardiman, Dennis Harding, Jean Harlow, Ian Harper, Mike Harris, Celia Harris, Hannah Harrison, Graham Harrison, Frances Harrison, Lee Harrison, Rachel Harrison, Dominic Harte, Laura Harvey, Jessica Harvey-Smith, Rodney Harward, Samantha Harwood, Liela Hathaway, Jonno Hauxwell, Hilary Hawkins, Pam Hayes, Simon Hayter, Charlie Head, John Hearn, Georgina Heath, Jill Heathcock, Anna Heck, Anita Heiberg, Kat Heiden, Charlotte Henderson, Fleur Henderson, Stroma Henderson-Reid, Jen Henry, Andrew Herbert, Christine Herd, Patricia Herranz, Ian Herriott, Mike Herron, Ann Hetherington, Rob Hick, Lorraine Hickman, Anneka Hicks, Michael Higdon, Elayne Higgins, Laura Higgins, Lian Higgott, Jacqui Hill, Adam Hillier, Nigel Hinds, Yoshihiro Hino, Louise Hislop, Emma Hocking, Alan Hodge, Norma Hodge, Eliot Hodges, Gilly Hodgkinson, John Hogan, Talle Hogrefe, Sue Holding, Megane Holl, Jennifer Holmes, Jonathan Holmes, Sue Holmes, Susan Holmes, Cols Hols, Dr Rachel Holt, Martin Holt, Luke Homan, Doug Hopper, Rob Horne, Craig Houchen, Martin Hough, Belinda House, Michael Houston, Phil. Howes, Jono Hoyer, Amelia Hoyt, Ronald Huckle, Julie Hughes, Janice Hughes, Carol Hughes, Sable Hughes, Richard Hull, Madeleine Humphrey, Mark Humphreys, Charlotte Hunt, Sally Hunter, John Hunter, A Hurley, Stephen Hurr, Nellie Hynes, Muhammad Ibrahim, Julian Ingleby, Neil Irving, Vickie Irwin, Susan Ison, Judy Jackman, Sian Jackson, Andrew Jackson, Paula Jacobs, J Jacobson, William Jacques, Chris Jagger, Lisa Jarrold, Steve Jayes, Andy Jefferies, Peter Jeffs, Alice Jennings, Jane John, Dylan John, Michael Johnson, James Johnson, Eleanor Johnson, Louise Johnson, Colleen Johnson, Elinor Johnston, Mark Johnstone, Mark Jones, Sara Jones, Ed Jones, Antony Jones, Penelope Jones, Allen Jones, Martin Jones, Pat Jones, Daniel Jordan, Jane Judd, Jyll Justamond, Siti Kala, Michael Kamp, Sharon Kampff, Sanj Kavanagh, Lj (Joelle) Keating, Kerstin Kehren, Nicola Kelly, Kayte Kelly, Orla Kelly, Stephen Kelly, Niamh Kelly, Carolyn Kennett, Randi Kepecs, Eileen Kerhouant, Declan Kerr, Barb Kerslake, Julia Kierepko, Jordan Kiley, Richard King, Christine King, Judith King, Adam King, Phil King, Diane Kinloch, Matthew Kinslow, Alanah Kirby, Wayne Kirk, Tom Kirkbride, Paul Kitchen, Josephine Kivlehan, Megan Klaar, Melanie Knight, Cameron Knight, Mary Knight, Richard Knight, Erin Knight, Gillian Knight, Richard Knights, Angela Knisely-Marpole, Eva Kolaczinski, Kate Kolaczinski, Kim Komp, Emi Koshino, Katrin Kugler, Vivek Kumar, Michelle Kusch, Anita Laird, Suzanne Lal, Yoyo Lam, David Lane, David Lang, Mark Lansbury, David Latham, Nick Latheron, Robert Latta, Peter Lawrence, David Lawrence, Helena Lawrence, Gillian Laws, Judith Lazell, Jeanette Lea, Anne Leakey, Pauline Leather, Paul Leighton, Helmar Leishman, Dustin Lendvay, Jane Lester,



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Rouse, Julia Rozanski, Julia Rozanski, Kathryn Rushton, Karen Russell, Lynne Russell, Jo Rutter, Sarah Ryan Frost, Sarah Rycroft, Ellie Rylance, Jennifer Sacher, Nigel Sadler, David Sakrison, Lauren Salter, Annie Samson, Henny Sands, Jason Sannegadu, Eric Sargeant, Julia Saunders, Mark Saunders, Annaliza Savage, Ian Sayer, Barbara Scanlon, Danielle Schaff, Amelia Scheil, Shelley Schermer, Margaret Schmeisser, Laurel Schneider, Sam Schoales, Connie Schoales, Amanda Schott, Ari Schuring, Emma Scott, Mac Scott, Ian Scott, John Scott, Anthony Scullion, Nigel Seal, Mary Seay, Sarah Sells, Miranda Semple, Katie Shanahan-Jones, Patrick Sharrocks, Thomas Shaw, Claire Sheehan, Michael Sheehan, Jessica Sheehan, Kate Sheerin, Lyndsey Shelley, Vicki Shenton, Nicholas Shepherd, Shigenori Shibata, Kaoru Shibata, Luann Shield, Bridie Shorthose, Ines Silva, Emily Simmons, Luke Simms, Clare Simpson, Juliet Simpson, Jo Simpson, Tom Sims, Gillian Sinclair, Lindsay Singh, Claire Skitt, Colleen Slater, Paul Slavin, Belinda Sleigh-Johnson, Alison Smalley, Ian Smart, Lynne Smethurst, Brianna Smetzer, Hugh Smith, Hannah Smith, Natalie Smith, Rachel Smith, Heather Smith, Sue Smith, Mark Smith, GräïInne Smith, Guy Smith, James Smith, Christine Snelling, Alessandro Soldi, Claire Solomon, Ed Sonnex, Colin Southall, Ian Sparbeck, Mark Spaulding, Catherine Speakman, Neil Spence, David Spencer, Juanita Spooner, Rhiannon Sprigg-Wiggins, Jasmina Stafford, Tony Stainsbury, June Stanley, Lisa Stanway, John Stark, Rachel Steendahl, Erin Stephen, Jo Stephenson, Mar Steven, Marjorie Stevens, Catherine Stevens, A Stevenson, Ashley Stevenson, Eleanor Stewart, Robin Stewart, Sheila Stewart, Colin Stewart, Martin Stickley, Amy Stocking, Meg Stockley, Ellie Stone, Andrew Stone, Claire Stone, David Streek, Mike Streetly, Margaret Strobl, Nick Stronach, Noella Suddaby-Watson, Fernando Suescun, Claire Sugden, Daniel Sumption, Phil Sutcliffe, Joan Sutherland, Diana Sweeney, Caroline Sweeting, Chris Swindells, Ewa Szeinduchert, Rebecca Tait, Sheena Takkenberg, Meryl Tanton, Deidre Tavares, Sheila Taylor, Sam Taylor, Sarah Taylor, Kevin Taylor, Naomi Taylor, Luisa Taylor, Rachel Teare, Camilla Temple, Genevieve Temple - Davies, Frances Tenison, Alexis Teplick, Geraldine Terry, Malcolm Thomas, Alan Thomas, David Thompson, Glenn Thompson, Lara Thompson, Zara Thompson, Jane Thompson, Scott Thompson, Helen Thomson, Pandora Thoresby, Michael Thornton, Sam Thornton, Lee Thurston, Hilary Tildesley, Rachel Tinker, Jeffrey Titmus, Keith Tokeley, Paul Tolan, Florence Tolhurst, S3Amus Tollitt, John Tomasi, Jessica Torres, Llewellyn Toulmin, Richard Towers, Christie Travelute, Carol Travers, Sarah Triemer, Matt Tuck, Richard Tucker, Logan Turchin, Susan Turner, Victoria Turner, Melanie Turner, Kieran Turner, Caroline Upton, Chess Usher, Tina Vallis, Annette Van Apeldoorn, Marike Van Beuge, A. Jay Van Der Reijden, Barbara Verardo, Laura Verney, Paul Vicente, Louis Vieira, Caroline Vile, Jeremy Vine, Donna Vitasovich, Anuhya Vuppala, Deborah Wakelin, Reighan Waldron, Adele Walker, Poppy Walker, David Wall, Symeon Waller, Fiona Walton, Tracy Ward, Naomi Warren, John Warren, Wendy Waters, Jay Watkin Beamond, Joan Watson, Malcolm Watson, Rebecca Watts, Andrew Waugh, Andrew Way, Claire Webb, David Webster, Caryl Weekley, Karen Wells, David Welsh, Andree Welsh, Gail Wenger, Maria West, Craig Westcott, Beatrice-Anne Westoby, Maria Wheatley, Leanne Wheeldon, Ruth Wheeler, Richard Whitaker, Linda White, Stephanie White, Gabrielle White, Rob Whitehead, Laurence Whitlock, Alice Whittington, Anna Whittington, Hana Whitty, David Wickham, Cindy Wiggins, Eloise Wilde, David Wilkins, Glynis Wilkinson, Andy Wilkinson, Anne Wilkinson, Ann Wilkinson, Stan Wilkinson, Michelle Williams, Heidi Williams, Carolyn Williams, Jerry Williams, Caroline Williams, Paula Williams, Charlotte Williams, Lee Williams, Mike Williamson, Rosemary Wilson, Stephen Wilson, Emma Wilson, Kierri Wilson, Miranda Wilson, Colin Wise, Andrea Witham, Richard Witham, Lulu Wolf, Frances Wolfe, Janice Wong, Georgia Wood, Peter Wood, Jo Wood, Jane Woodall, Paul Woodham, Kay Woodhouse, Lindsay Wookey, David Worsnop,



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Executive Summary

Citizen science has evolved from a primarily educational activity into a powerful tool for Nature Recovery, uniting people, data, and technology to drive informed environmental decisions. However, its potential remains constrained by several key challenges: most environmental citizen science initiatives operate in specialised niches with narrow geographic scope, creating siloed knowledge that rarely extends beyond immediate project teams. This fragmentation has resulted in limited data interoperability, restricted accessibility, and financial barriers to wider adoption in Nature Recovery efforts.

The Natural Capital and Ecosystems Assessment (NCEA) programme, through Natural England, sought to address these limitations by exploring whether redirecting investment toward standardisation and knowledge-sharing across public environmental studies could enhance policymakers' capacity to integrate natural capital approaches into recovery strategies. DigVentures was selected to lead this investigation through the Citizen Science Local Pilots project (CSLP Lot 1 – Northumbria), developing collaborative solutions to unlock citizen science's full potential for landscape-scale environmental monitoring and restoration.

The DigVentures project builds on Deep Time – a collaborative mapping platform for natural and cultural heritage that enables communities and landowners to gather essential data for adopting natural capital approaches, regenerating landscapes, and addressing climate challenges. This platform integrates two core technologies: a participatory Geographic Information System that allows citizens to map various data sources (satellite, drone, and LiDAR) alongside desk and field data, and a learning management system that equips non-specialists with the skills to make scientifically valid contributions.

Through collaborative design sessions with delivery partners, the project team explored how to effectively embed a natural capital approach into an Earth Observation (EO) model of Citizen Science. This process resulted in the development of five action-focused pilots (or 'missions') created in partnership with key regional stakeholders: North Pennines National Landscape, Northumberland National Park, Northumberland Wildlife Trust, the National Trust, Durham Wildlife Trust, and Northumberland Coast National Landscape.

The results of these missions are summarised in this report, based on detailed assessment of spatial and participant data, followed by recommendations for further development and implementation of EO-based citizen science and natural capital monitoring. Key highlights include:

- Project participants generated comprehensive habitat mapping datasets across five distinct regions of Northumbria, creating over 58,000 individual habitat polygons covering approximately 4,800 square kilometres in just five months.
- Quality assessment of the four Deep Time datasets that mapped multiple habitats revealed that Citizen Scientist data matched or outperformed machine learning-derived baseline datasets 88% of the time.
- Recruitment attracted 1,208 applicants from 32 countries, with 489 Futureonauts completing training supported by 41 'Mission Leaders' (experienced participants given additional training to assist community members).
- Participants represented diverse socioeconomic backgrounds with remarkable age diversity—people aged 17-89 contributed despite the platform's technical nature.



- Participant self-assessment revealed that Citizen Scientists dedicated approximately 9,000 hours to the project, equivalent to over five years of work for one professional.
- 80% of participants expressed interest in returning for more Deep Time missions, with high interest in both Natural and Cultural Heritage mapping projects.
- 68% of participants reported feeling an increased connection to the mission study areas through their contribution to the CSLP project.
- The project increased optimism for the future and interest in nature recovery projects, with 91% of participants reporting they were inspired to make further daily changes to positively impact the environment because of their participation.

The five pilot missions conducted with regional nature recovery partners have unequivocally demonstrated the transformative potential of an EO model of citizen science paired with AI derived baseline habitat mapping. The following recommendations are made to help refine the work presented here:

Deeply embedding Citizen Science into Professional Workflows

The project has successfully implemented an AI and EO model of citizen science to generate professional grade data outputs and ultimately linking grassroots action with professional environmental management needs. Additional collaborative design sprints with delivery partners are now recommended, developing protocols for deeply embedding citizen-generated data into organisational workflows, creating a cyclical process of field verification, refinement, and ongoing habitat monitoring.

Enhanced Quality Assurance Methodology

While Living England ground survey data provided a useful primary baseline, this approach only evaluated habitat identification at specific points rather than assessing the full value of citizen contributions. Enhanced quality metrics are recommended (fidelity, accuracy, completeness, recency) building on the QA methodology prototyped on mission 1.

Citizen Micro-actions and Nature Recovery

The project has demonstrably influenced participants' environmental behaviours. Additional training modules should be developed that provide concrete ways for citizens to contribute to landscape recovery from home, converting climate anxiety into practical engagement through accessible 'micro-actions' that advance nature recovery while reinforcing personal impact.

Strategic Communications and Policy Change

Working across diverse landscapes from coastal zones to upland moors, citizen participants have mapped habitats at unprecedented scale and pace while experiencing profound shifts in their connection to nature. These compelling results advocate for policy changes that formally recognise Earth Observation citizen science as a legitimate methodology within environmental monitoring frameworks. A strategic communications plan is recommended, emphasising how this approach bridges professional conservation priorities with meaningful public participation in nature recovery, creating a powerful pathway for inclusive, sustainable landscape transformation.



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1 INTRODUCTION

1.1 Citizen Science Local Pilots and the Deep Time Platform

- 1.1.1 Deep Time is a new digital platform combining Spatial AI and Earth Observation Data (EO) with citizen-led habitat and historic environment monitoring, providing a bridge between the organisations responsible for landscape transformation projects, and the citizens wishing to get involved. This interim summary report summarises the initial results of Deep Time's implementation as part of the Northumbria region Citizen Science Local Pilots project (CSLP), commissioned by Defra and Natural England's Natural Capital and Ecosystems Assessment (NCEA) programme.
- 1.1.2 Through collaborative design sessions with delivery partners, the project's principal challenge was to explore how a natural capital approach could be embedded into an applied EO model Citizen Science. Five action focussed pilots (or 'missions') were then developed in partnership with North Pennines National Landscape, Northumberland National Park, Northumberland Wildlife Trust, the National Trust, Durham Wildlife Trust and Northumberland Coast National Landscape.
- 1.1.3 The results of these missions are summarised below, based on a detailed assessment of spatial and participant data, followed by recommendations for further development and implementation of EO-based citizen science and monitoring of natural capital.

1.2 Project Background

- 1.2.1 From tracking the pollution in our rivers to mapping habitats from satellite data, citizen science – where members of the public participate in scientific research – has grown from a casual hobby into a vital tool for environmental recovery. Volunteer researchers are helping fill vital data gaps in our understanding of the natural world, providing valuable insights to help protecting and restoring our landscapes. But what if we've barely scratched the surface of citizen science's potential? What if citizen science could do more?
- 1.2.2 Traditional citizen science projects often operate in isolation from each other, with valuable environmental data trapped in separate databases and platforms. This fragmentation limits our ability to build the comprehensive picture needed for effective nature recovery. While citizen science projects evidently demonstrate the power of public engagement, their wider impact on professional workflows is often constrained by both technical barriers inhibiting everyday participation and limited reach beyond traditional volunteer demographics.
- 1.2.3 The concept of natural capital has been proposed as a potential 'coordinating' tool for nature recovery, moving beyond the shallow framing of landscape in purely economic terms to encompass the ecosystem services that landscapes provide to humankind. A range of Nature-based Solutions have been devised to tackle the decline in natural capital, with new initiatives like Biodiversity Net Gain and Local Nature Recovery Strategies incentivising public and private investment in nature recovery.



- 1.2.4 But these ambitious policies face several critical obstacles, including a lack of comprehensive baseline data about habitats and historic environments; siloed professional structures that treat natural and cultural heritage as separate entities; and barriers to citizen participation and decision-making, diminishing the potential value of the historic and natural landscape for people.

2 METHOD AND APPROACH

2.1 Project Workflow

- 2.1.1 By empowering citizens to map historic landscapes and ecological habitats using satellite imagery, Deep Time offers the promise of aligning grass roots action, professional environmental management needs and broader conservation policies and strategies.
- 2.1.2 A high-level workflow was devised to realise this ambition (Figure 1), framing citizen participation as a six stage 'infinity loop' feedback model: (1) participants joined a training cohort delivered through a structured online course to recognise, annotate and describe Habitats from EO data, supported by workshops and twice weekly newsletter; (2) participants joined cohort 'missions' on predefined landscape areas with AI derived baseline habitat mapping provided by Living England, learning about the specific nature recovery challenge they were solving; (3) participants recorded features, enabled with a web accessible GIS and chat tool, supported by a single-track validation system; (4) represented our inhouse data repository, with a professional quality audit of citizen data against Living England ground survey points.
- 2.1.3 Stages (5) and (6) were beyond the scope of the present project, but envisaged a field checking stage (5), further refined into actionable knowledge in stage (6) with refined and augmented data passing back to in house repository at stage (4), and periodically recommencing citizen monitoring again with stage 1.

2.2 Participant Recruitment and Training

- 2.2.1 The participant recruitment strategy focused on achieving both breadth and depth – expanding participation beyond traditional enthusiast communities while fostering meaningful, sustained engagement with predominantly new audiences. This approach allowed the project to investigate effective methods for recruiting and maintaining participant involvement in citizen science initiatives, particularly through non-financial engagement mechanisms and social dynamics. By examining these factors, the project sought to identify essential elements for successfully scaling citizen science projects and broadening public participation in nature recovery.
- 2.2.2 Recruitment was highly successful, attracting 1,208 applicants from 32 countries, with 489 Futureonauts completing the training supported by 41 Mission Leaders (experienced participants given extra training to help and support other members of the community). At the outset of the first mission there were 315 graduates and by the final mission, this had grown to 484 unique participants completing the training course. This group was diverse, with equal representation across age, gender, socioeconomic status, 14% from non-white backgrounds, and more than half having

no prior experience (see Section 4). In total, 167 citizen scientists participated in the North Pennines National Landscape mission, 162 on the Hadrian's Wall corridor, 102 at Wallington Estate, 72 at Brightwater and 82 on the Northumberland Coast National Landscape, making up a total 585 FutureNaut places filled across the missions.

- 2.2.3 A comprehensive training program prepared participants for habitat mapping through a self-paced course covering GIS fundamentals, nature recovery principles, and habitat identification (Figure 2). The 6–10-hour curriculum combined written materials (Fig. 2a, 2b), instructional videos, and a Habitat Guide focused on interpreting Earth Observation imagery (Fig 2d). Upon completion, participants gained access to all project missions (Fig 2e), supported by live Q&A sessions at the start of each mission and an integrated chat system facilitating peer collaboration and staff support (Fig 2c). The platform's communication features include dedicated chat channels for training, individual missions, and Mission Leaders, which collectively generated over 2,100 messages throughout the project. This multi-layered support structure ensured participants could effectively contribute while continuing to develop their skills and confidence.

3 RESULTS AND ANALYSIS – SPATIAL DATA

3.1 Data Quantity and Quality

- 3.1.1 Through the accumulated CSLP project missions, citizen scientists generated comprehensive habitat mapping datasets across five distinct regions of Northumbria (Figure 3), totalling over 58,000 individual habitat polygons covering approximately 4,800 square kilometres. The largest single dataset was created for the Hadrian's Wall corridor, where participants mapped over 20,800 polygons across 1,120 square kilometres. In the North Pennines National Landscape, 7,430 water bodies were identified across 2,369 square kilometres, while the Wallington Estate study documented 6,456 habitat polygons over 315 square kilometres. The Brightwater Landscape mapping yielded 11,646 polygons across 483 square kilometres and finally, participants mapped 12,364 polygons across 593 square kilometres of the Northumberland Coast.
- 3.1.2 Quality assessment (QA) of the citizen science data focused on comparison with Living England ground survey – the most reliable professional baseline available. This was based on a presence/absence methodology, evaluating citizen habitat identification accuracy by comparing Deep Time results against both field survey data and existing datasets including Phase IV and LE 2022-2023 Habitat Probability maps (see Figure 4 and Appendix A). The project was also given access to data gathered by the England Ecosystem Survey from a selection of monads across the study district. However, the EES data consistently corresponded with the same geographical locations as the LE ground survey data and represented a significantly smaller sample, so was not utilised for the purposes of reporting.
- 3.1.3 The QA methodology (see Appendix A) was constrained by the variable number of grids containing Living England Ground Survey points available for each mission, with 54 reference grids in the Hadrian's Wall area, 71 in the Northumberland Coast region, 9 at Wallington Estate, and 2 in the Brightwater Landscape. In addition to a lack of



coverage, other shortcomings of this QA methodology were identified, particularly the binary focus on presence/absence of ground control points and failure to encompass the nuance of citizen science polygons (such as fidelity, accuracy, completeness and recency). This raised questions on the fitness for purpose of the presence/absence QA methodology in relation to augmented citizen science EO data, and an alternative quality methodology was prototyped for the North Pennines mission (described further below).

3.2 Mission 1: North Pennines

- 3.2.1 As the first mission in the CSLP project, the North Pennines National Landscape mapping task was designed to introduce participants to the Deep Time process with a simpler task than would be completed in later missions. Citizen Scientists were asked to identify and map just a single habitat type – standing water. The North Pennines National Landscape was interested in creating a dataset representing the standing water habitats on the land under their management to help in their ongoing Nature Recovery projects like eDNA sampling. This simpler task also ensured the new platform tools and training methodologies could be tested within a controlled set of parameters.
- 3.2.2 Participants were asked to map the maximum extent of any standing water and dry seasonal water bodies that were visible on the Earth Observation imagery. The map layers provided in the platform were: The Living England Phase IV Habitat Probability Map, polygons representing potential water bodies derived through LiDAR reflectivity data, Aerial Photography of Great Britain 25cm and a LiDAR Digital Terrain Model. Using these 4 layers, CSLP participants mapped 7,430 bodies of standing water over 2,369 square kilometres of upland landscape (Figures 5, 6) in just two weeks – half the time that had been allotted for the mission.
- 3.2.3 Given the specialised nature of this mission, Living England ground control points proved inadequate for quality assessment, necessitating a bespoke QA methodology for the mission (see Appendix B). Professional quality assurance of the open water habitat data was conducted by the North Pennines National Landscape (NPNL) partnership team. This modified assessment method, based on the established Deep Time cultural heritage QA technique, evaluated three metrics for each feature, calculating a percentage score for each grid square: Fidelity – whether a drawn polygon represented a qualifying water body, Accuracy - whether the polygon met NPNL drawing standards, and Completeness - whether all water bodies within a grid were recorded.
- 3.2.4 A random sample of 50 grid squares underwent evaluation using this methodology and yielded positive outcomes for Deep Time, with aggregated quality scores across the 50 random grids showing strong performance: 85.3% for Fidelity, 76% for Accuracy, and 82.4% for Completeness (see Appendix C). Testing the methodology revealed several refinement opportunities to enhance scoring nuance. Notably, adding a fourth metric of 'Recency' would be valuable, evaluating the age of source data and reference materials informing the records. For habitat and ecological information, more current data provides more valuable insights, making this temporal

assessment of both baseline and Deep Time data a beneficial addition to the quality framework.

3.3 Mission 2: Hadrian's Wall

- 3.3.1 The Hadrian's Wall mission focussed on the area bordering the section of Hadrian's wall that lies within Northumbria, extending just under 10 kilometres to the north and south of the wall corridor. The large size of the study area meant that participants gained experience examining a variety of different locales from the urban city centre of Newcastle at the eastern end of the area to the agricultural fields, grassland, peatland and woodland towards the west.
- 3.3.2 Participants were given six data layers to help them identify 16 habitat types based on the UK Biodiversity Action Plan (UKBAP) habitat types, consistent with the categories used by Living England for their Habitat Probability Maps (see Appendix A, D). Available data layers included Living England Phase IV Habitat Probability Map, a LiDAR derived Canopy Height Model representing vegetation/tree heights (also supplied by Living England), a LiDAR Digital Terrain Model, the Aerial Photography of Great Britain (APGB) 25cm, and two satellite imagery composite mosaics made up of seasonally focused images taken at spring or autumn, also supplied by Living England. Using these layers participants identified and mapped over 20,800 habitat polygons across the 1,120 square kilometres of the study area (see Figure 7).
- 3.3.3 Within the Hadrian's Wall mission area, Living England Ground Survey points were found within 54 of the 1,120 grids completed by participants. Of these grids, 35 were randomly selected for quality assessment representing 3% of the total grids mapped (see Appendix A: M2).
- 3.3.4 Presence/absence assessment of the Hadrian's Wall grids revealed strong performance in habitat identification accuracy when compared to the baseline professional datasets. Of the 35 Deep Time grids assessed, 15 (43%) achieved a perfect habitat match with the ground survey data points, representing correspondence between the CSLP Citizen Scientists and the environmental professionals who completed the ground survey. The Citizen Scientists outperformed the machine learning derived mapping in this respect, with the LE 2022-2023 map aligning with 14 grids where with ground survey points, and the Living England Phase IV Habitat Probability Map aligning with 13 grids.
- 3.3.5 When compared to the Living England Habitat Probability Maps, the CSLP Citizen Scientists created more accurate habitat identifications than both the Phase IV and the LE 2022-2023 map in 17% of cases (6 grids). In 26% of the grids (9 in total), all datasets scored equally. In 7 of the grids (20% of total) the Deep Time data was better than one of the Living England datasets and equal in accuracy to the other. In 4 grids (11%), The Deep Time data came between the LE maps in accuracy, one Deep Time grid (3%) tied with a LE map for the second most accurate, and 8 (23%) Deep Time grids scored the poorest of the three datasets.
- 3.3.6 Overall, 63% of Deep Time grids either matched or outperformed both mapping approaches. A further 14% ranked second in accuracy, while the remaining 23%



showed lower performance. In consequence, 77% of the assessed Deep Time grids proved either more accurate than or equal to one of the existing professional datasets.

3.4 Mission 3: Wallington

- 3.4.1 The Wallington Estate mission was designed to map habitats across the National Trust's Wallington Estate and surrounding area. This area is broadly made up of woodland and agricultural land. The smaller mission area provided an opportunity for participants to focus on improving their drawing skills and try for an increased quality of mapping after their first experience mapping comprehensive habitats on mission 2.
- 3.4.2 As with mission 2 (and all following missions) participants were given six data layers to help them identify 16 habitat types based on the UK Biodiversity Action Plan habitat types used by Natural England for their Phase IV and LE 2022-2023 mapping (see Figure 8). Using these layers participants identified and mapped over 6,456 habitat polygons across the 315 square kilometres of the study area.
- 3.4.3 Living England Ground Survey points were identified within 9 of the 315 grids completed by participants on the Wallington mission. All 9 of these grids were selected for quality assessment representing 3% of the total grids mapped (see Appendix A: M3). Of the 9 Deep Time grids assessed, 4 (44%) achieved a perfect habitat match with the ground survey data points, representing total agreement between the CSLP Citizen Scientists and the environmental professionals who completed the ground survey. The Citizen Scientists performed equally well as the Phase IV mapping which also had 4 grids aligned with the ground survey and outperformed the LE 2022-2023 data which had 2 grids (22%) in complete agreement with the ground survey points.
- 3.4.4 When compared to the Living England Habitat Probability Maps, the CSLP Citizen Scientists created more accurate habitat identifications than both the Phase IV and the 2022-2023 map in 11% of cases (1 grid). In 22% of the grids (2 in total), Citizen Scientists performed equally as well as both the Living England maps. In 4 of the grids (44% of total) the Deep Time data was better than one of the Living England datasets and equal in accuracy to the other. In the final two grids, Citizen Scientists tied with one of the LE maps for the second most accurate.
- 3.4.5 Overall, 78% of Deep Time grids either matched or outperformed both mapping approaches. A further 22% ranked second in accuracy. In summary, for 100% of assessed grids the Deep Time data proved either more accurate than or equal to one of the existing professional datasets.

3.5 Mission 4: Brightwater

- 3.5.1 The Brightwater mission was delivered in partnership with the Durham Wildlife Trust, mapping 16 habitat types across lowland County Durham, including wetlands, woodlands agricultural land and urban areas. Using these layers participants mapped 11,646 polygons over the 483 square kilometres of the study area (see Figure 9).
- 3.5.2 The Brightwater mission analysis was limited by having only two grids containing Living England ground survey data points (see Appendix A: M4). While one grid



achieved perfect alignment with Living England survey data and outperformed both Habitat Probability Maps and Living England 2022-2023 datasets, and the other ranked second in accuracy it is difficult to assess performance based on only a 0.4% sample size. For Brightwater, like the other mission areas, further professional quality analysis with a validation and verification methodology examining data characteristics such as polygon accuracy and reference data recency, will help to quantify and measure Deep Time outputs against pre-existing baseline data and alternative habitat datasets.

3.6 Mission 5: Northumberland Coast

- 3.6.1 The final mission was focussed on the landscape inland from the Northumberland Coast National Landscape and the Northumberland Wildlife Trust's interests at Wilder Druridge. This mission gave participants the opportunity to learn to identify and map coastal habitats that were not part of the previous missions.
- 3.6.2 Participants were given six data layers to help them identify 16 habitat types based on the UK Biodiversity Action Plan habitat types used by Natural England for their Phase IV and LE 2022 - 2023 mapping. Using these layers participants identified and mapped over 20,800 habitat polygons across the 1,120 square kilometres of the study area (see Figure 10).
- 3.6.3 Within the Northumberland Coast mission area, Living England Ground Survey points were found within 71 of the 593 grids completed by participants. These represent 12% of the total grids mapped and were all selected for quality assessment. (see Appendix A: M5). QA of the Northumberland Coast grids revealed strong performance in habitat identification accuracy when compared to the baseline. Of the 71 Deep Time grids assessed, 42 (59%) achieved a perfect habitat match with the ground survey data points, representing total agreement between the CSLP Citizen Scientists and the environmental professionals who completed the ground survey. The Citizen Scientists outperformed the machine learning derived mapping in this respect, with the Living England Phase IV Habitat probability map having 34 grids where all the ground survey points were matched, and the LE 2022-2023 map having 35 grids in perfect agreement.
- 3.6.4 When compared to the Living England Habitat Probability Maps, the CSLP Citizen Scientists created more accurate habitat identifications than both the Phase IV and the LE 2022-2023 map in 15% of cases (11 grids). In 42% of the grids (30 in total), all datasets scored equally. In 17 of the grids (24% of total) the Deep Time data was better than one of the Living England datasets and equal in accuracy to the other. In 3 grids (4%), the Deep Time data came between the LE maps in accuracy, 4 Deep Time grids (6%) tied with a LE map for the second most accurate, and 6 (8%) Deep Time grids scored the poorest of the three datasets.
- 3.6.5 Overall, 82% of Deep Time grids either matched or outperformed both mapping approaches. A further 10% ranked second in accuracy, while the remaining 8% showed lower performance. In 94% of the assessed grids, the Deep Time data proved either more accurate than or equal to one of the existing professional datasets.



4 RESULTS AND ANALYSIS – CITIZEN EVALUATION

4.1 Evaluation Methodology

- 4.1.1 A comprehensive evaluation framework was embedded into the project workflow to understand participant demographics, motivation and experience. Quantitative and qualitative data was collected through a pre-training survey (1,208 respondents, 100% completion rate), a post-training survey (489 respondents, 100% completion rate) and post-project survey for a statistically valid sub-sample of Futurenauts (150 respondents, 31% completion rate). These surveys employed both closed and open-ended questions using a five-point Likert scale to assess demographics and measure broader impact metrics (see Appendix E, F & G). This iterative feedback process will inform future mission development, ensuring the platform evolves to meet participant needs and foster sustained engagement with the Deep Time community.

4.2 Inclusion

- 4.2.1 Pre-training evaluation was designed to understand the Citizen Scientists who took part in the project and to evaluate the pilot's success in attracting and maintaining the diverse group of participants that is integral to a Collective Intelligence approach. Measuring the diversity of the cohort also demonstrated whether the CSLP project was successful in broadening participation in citizen science.

- 4.2.2 Through analysis of participant surveys, the project was shown to have succeed in attracting a diverse, global audience. Participants joined from 32 different countries, unrestricted by geographic proximity to study areas by the nature of the online platform (see Figure 11). While the project attracted a slightly lower percentage of non-white individuals (14%: Figure 12a) than the average UK demographic of 18%, this number represented a significant improvement on the typical non-white participation in environmental citizen science projects (Pateman et al 2021).

- 4.2.3 Gender representation also showed a notable shift from traditional citizen science demographics, with women making up 55% of participants and 1% using gender-neutral pronouns (Figure 12b) – an improvement over the male-dominated participation typically seen in similar projects (Pateman et al 2021). The platform's flexible, asynchronous approach enabled participation across varied occupational backgrounds, with no single professional group dominating the cohort (Figure 12c).

- 4.2.4 Some participants, like Aalia, a 41-year-old actor, commented that the simplicity of the technology was an important factor in their participation:

'I've never been a big technology person. It's been challenging to find ways to use tech and have it not feel like work. Deep Time gave me the opportunity to have fun using my computer and gave me the sense that I was contributing to something important.'

- 4.2.5 This sentiment captured the importance of citizen-centric design in reducing barriers to participation, encouraging a wide age range of participants (from 17 to 89 years old) to get involved despite the technical nature of the platform (see Figure 12d).



4.3 Participation

- 4.3.1 In addition to inclusivity, participant surveys were designed to explore both breadth and depth of engagement. Specifically, was the project successful in engaging groups new to citizen science and nature recovery projects, and did engagement deepen over time, inspiring citizen participation throughout and beyond the project?
- 4.3.2 The survey data revealed that the project was successful in broadening the audience for Citizen Science and Nature Recovery initiatives with 70% of participants stating they were new to this type of project. Of these, 49% had no prior experience and 21% had only participated in a previous DigVentures' project (see Figure 13). Breadth of engagement can also be extended to data creation, measuring deviation from the established trend in citizen science where 20% of participants generate 80% of the data. This was improved upon across the missions, where 10,114 grid squares were completed. In total these were completed by 60 participants, meaning 80% of the results were generated by 25% of the total cohort. However, when the focus is on polygons rather than grid squares, 16% of participants produced 80% of the data. This is influenced by the fact that the top contributor created nearly twice the number of polygons (24,162) to the next most prolific participant (14,544).
- 4.3.3 Depth of engagement was tracked through the number of missions participants took part in, and the average amount of time they dedicated to the project. Starting with 315 graduates at the first mission, the participant pool grew to 492 by the final mission, due to continuous, open registration and self-guided training. Mission participation varied across the study areas, with 167 participants in the North Pennines, 162 at Hadrian's Wall, 102 at Wallington Estate, 72 at Brightwater, and 82 at Northumberland Coast (see figure 14a). While these numbers show a decline in later missions, this was expected as participants could choose which missions to join based on their interests and availability. The advantages of this approach were illustrated in a comment from Meaghan a 54-year-old home educating parent:

'I intended to participate in two missions, and did so, though not the two I had planned. Unexpectedly at home more than usual in the autumn, I did an extra mission then; but I had less free time than expected in early 2025, so I was unable to do the 5th mission. The flexibility to opt into an extra mission in the autumn kept me sane when stuck at home for a month with a sprained ankle – perfect!'

- 4.3.4 This demonstrates how the flexibility in participation allowed for a deeper engagement for some participants, electing to contribute data to multiple different missions (Figure 14a – f). Participants were also asked during the application process to dedicate a minimum of 2 hours per week during the training phase and subsequent live missions. When asked to self-assess in the post-experience survey, most participants exceeded this number, with just 37% of participants stating they spent between zero and two hours a week on the project. Over a third of participants (49 individuals) spent 2-4 hours and an impressive 22% (33 individuals) of participants at minimum doubled the requirement, dedicating 4-10 hours, 5% (7 individuals) devoted 10-20 hours to the project, and 2% (3 individuals) contributed 20-30 hours. Two participants (1%) self-reported over 30 hours of weekly engagement (see Figure 15).



This can be extrapolated as approximately four and a half hours per participant a week, totalling over 9,000 hours dedicated to the missions over the project – the equivalent of 1,153 workdays or 5.2 years of work based on standard employment assumptions.

4.4 Motivation

4.4.1 The pre-training survey asked participants why they wanted to take part in the project, aiming to illuminate their motivation for joining and to understand what they were hoping to gain out of participation. The post-project survey questions were designed to gain an insight into whether participants felt the project had met their initial expectations and whether they had been motivated to participate in future Deep Time initiatives.

4.4.2 The data revealed that the most common motivation for joining the project was a previous positive experience with a Deep Time project, with 21% of registrants citing this as their main reason for joining. Learning opportunities attracted 17% of participants, matching the 16% who were motivated by care for historic and natural landscapes. Notably, 13% of participants valued the online format specifically, as it provided accessibility that traditional in-person projects could not offer (Figure 16).

4.4.3 This is evidenced by a comment made by Lisa, a 68-year-old retiree, in the post-project survey: '[The thing I most enjoyed about participating was] the feeling of doing something useful from home - I've got caring responsibilities and it's difficult to get out and engage in a more practical way.' The flexibility of online participation was a key motivation, enabling more people to support a cause they believed in but may not otherwise have been able to contribute to. Additionally, Sheila, 72, said; 'I am interested in continuing to learn and develop and DigVentures has offered me the best opportunities since I left school in 1969.' Entwined with the motivational drive of contributing to a virtuous cause, participants perceived getting something in return – in this case the intangible acquisition of skills and opportunity.

4.4.4 In the post experience evaluation, 85% of participants rated Deep Time as a good or very good way to learn new skills (Figure 17a); participants also felt that Deep Time was a good way to learn about the environment (88% good or very good; Figure 17b) and to get involved with nature recovery (70% good or very good; Figure 17c). Participants were also asked whether they were likely to participate in future Deep Time projects, with 80% of participants (120 individuals) responding that they were either likely or extremely likely to participate again (Figure 18a). Bringing this statistic to life, Ben, 52 said:

'I suffer with depression and anxiety, yet Deep Time somehow gives me the freedom I seldomly feel in real life - I've even treated myself to an all singing, all dancing desktop pc ready for this years' projects - I've also taught myself the very basics of QGIS.'

4.4.5 When asked about the types of future Deep Time missions they would be interested in joining, 73% of participants (109 individuals) were interested in joining in Natural Heritage based missions, with 17% of those saying they were extremely likely to participate (Figure 18b). Similarly, 92% of participants were interested in future



Cultural Heritage based missions and 73% of these said they were extremely likely to participate (see Figure 18c).

4.5 Perception and Behaviour Change

- 4.5.1 Post-participation qualitative evaluation sought to investigate shifts in participants' sense of connection to landscape and study areas, their comprehension of climate change dynamics, and their perceived role in catalysing climate-positive action (Figure 19). Prior to commencing, 34% of participants strongly agreed they felt a connection to their place of residence (404 individuals), while 45% acknowledged some level of connection (538 individuals; Figure 19a). Connection to the mission areas was less strong with 16% of participants (187 individuals) strongly agreeing, and 35% of participants (423 individuals) acknowledging some level of connection (Figure 19b).
- 4.5.2 After participation, 37% of respondents agreed that their connection to their place of residence had increased, 10% (15 individuals) strongly and 27% (41 individuals) acknowledged some level of increase (Figure 19c). Over two thirds (68%) of participants felt their connection to the mission areas had increased with 20% of respondents (30 individuals) strongly agreeing and 48% (72 individuals) agreeing to some level of increase (Figure 19d). Illustrating this increased connection to place, Theresa, a retired public rights of way officer, 73, said Deep Time helped her to '[appreciate] the landscape of parts of UK I don't know, and see the change that has happened in last 20 years' and Katherine, 70, a retired office manager said she 'enjoyed learn[ing] a lot, exploring (remotely) regions [she had] previously known very little about' and "contributing [...] to expansion of knowledge about these areas.'
- 4.5.3 The Deep Time training program aimed to educate participants about environmental threats and landscape management challenges while measuring shifts in climate-related perceptions and behaviours. Post-training and post-participation evaluation surveys were designed to explore participants' climate change perceptions and potential for behavioural shifts.
- 4.5.4 Significant levels of climate anxiety were expressed in the post-training survey with 94% of graduates saying they had some level of climate anxiety (see Figure 20a). Specifically, 29% indicated a little anxiety (143 individuals), 46% felt somewhat anxious (225 individuals) and 19% said they were very anxious (94 individuals). While most of the individuals who completed training stated that participation in training hadn't affected their levels of anxiety, 24% of participants (117 individuals) noted a decrease in anxiety and 9% (46 individuals) felt their anxiety had increased (Figure 20b).
- 4.5.5 Building on the earlier questions, the post-participation survey asked participants whether participation in the project had affected their level of anxiety around the potential impacts of climate change on their life. Most participants (74% or 111 individuals) reported no change; 4% (6 individuals) reported a significant increase; and 15% or 23 individuals reported a slight increase. Conversely, 6 participants (4%) felt a small decrease in anxiety and a single individual felt a significant decrease in anxiety (see Figure 21a).
- 4.5.6 This survey also explored whether participation had affected individuals' confidence in their ability to effect positive change. Over half of participants felt an increased



confidence, with 11% of participants (16 individuals) felt a significant increase and 42% (63 individuals) noted some level of increase (Figure 21b).

4.5.7 Post-training evaluation revealed significant positive impacts: 27% reported increased interest in local climate impacts, while 22% felt motivated to join other climate initiatives. Perhaps most significantly, 25% expressed greater optimism about the future, (see Figure 22a). This survey also showed that over the seven months of the project, a remarkable 91% of participants had been inspired to make further daily changes to have a positive effect on the environment (Figure 22b). Of these, 22% (33 individuals) stated they now made more daily eco-friendly choices; 21% (31 individuals) were inspired to spread awareness to others; 19% (29 individuals) chose more sustainable products and services; 13% (20 individuals) connected more with nature; 7% (11 individuals) started volunteering for environmental causes; 5% (8 individuals) joined other environmental action communities; and 4% (6 individuals) began to advocate for policy change (Figure 22b).

4.5.8 Ian, a project manager, 52, said his participation in Deep Time had inspired him to 'pick up a previous project on ancient woodlands we'd created at work and hand it off to a youth awareness group who were looking for ancient woodland mapping tool for their project', demonstrating the ripple effect that projects promoting climate action can have. Jing, a student, 21 said she has even 'started considering the environmental sector for future career' because of her participation in Deep Time.

4.5.9 Both these comments show the ripple effect that the project has had for participants, providing concrete ways to contribute to landscape recovery from home, and helping convert general climate anxiety into practical engagement. The ability to make meaningful contributions appears to be a factor in reducing eco-anxiety, with participants gaining both knowledge of environmental challenges and practical tools to address them. This practical engagement has also had the effect of inspiring a significant portion of participants to get even more involved in climate change mitigation efforts, underlining the value of providing additional opportunities for individuals to contribute beyond the Deep Time platform.

5 CONCLUSION

5.1 Overview

5.1.1 Over the course of the five missions, Citizen Scientists mapped habitats across over 4,800 square kilometres in five distinct regions of Northumbria. The participants created over 58,000 polygons and dedicated over 9,000 hours to the project demonstrating a sustained engagement over the five months of live missions.

5.1.2 Quality assessment of the multiple-habitat datasets created by participants showed that the Citizen Scientist data was equal to or better than existing machine learning derived datasets 88% of the time. This shows a clear benefit to citizen science where there is a demonstrable social benefit in addition to creating quality data that can be used to make decisions about land management and Nature Recovery.



- 5.1.3 The project succeeded in engaging a more diverse audience than is expected in Citizen Science projects, attracting 1,208 applicants from 32 countries, various socioeconomic backgrounds and across all age groups from 17 to 89. This diversity represents a broadening of the inclusivity of Citizen Science for the environment. Participants were motivated by a variety of factors to get involved and the experience was widely regarded as a valuable learning experience and participants see Deep Time as worthwhile community to be a part of both for social value and the feeling of contributing to a project that is working to critical environmental challenges.
- 5.1.4 Notably, 68% of participants said they felt an increased connection to the mission areas demonstrating that even through remote online engagement, Deep Time had the ability to foster a connection between people and the environment. This increased connection is an element of the projects remarkable ability to not only maintain engagement with participants, but to inspire further participation with Deep Time and beyond. Over three quarters of participants expressed a desire to participate in future Cultural and Natural Heritage projects with Deep Time and an extraordinary 91% of participants felt inspired by the project to make changes in their life for the benefit of the environment.

5.2 Recommendations

- 5.2.1 Deep Time successfully bridges grassroots action with professional environmental management and broader conservation strategies. While integrating landscape data into partner workflows exceeded the project scope, the intended model features field verification, refinement into actionable insights, and a cyclical process where enriched data flows back to repositories before citizen monitoring recommences. Future collaborative design sessions with delivery partners should develop effective protocols for embedding this valuable data into organizational workflows, ensuring maximum utility and impact for nature recovery initiatives.
- 5.2.2 Quality assessment of citizen science data primarily relied on comparison with Living England ground survey data – the most reliable professional baseline available for EO data. However, this approach only evaluates correct versus incorrect habitat identification at specific ground control points, failing to capture the nuance and comprehensive nature of citizen-generated polygons. Due to disparities in coverage and limitations in evaluating sophisticated quality dimensions (fidelity, accuracy, completeness and recency), an alternative quality assurance metric was prototyped during the North Pennines mission. Future project iterations should implement this enhanced QA model to supplement the limited baseline provided by ground control points, enabling more holistic evaluation of citizen science contributions.
- 5.2.3 Deep Time successfully aligns grassroots action with professional environmental management and broader conservation policies. By educating participants about nature recovery and engaging them in meaningful work, the project has demonstrably influenced environmental behaviours, prompting participants to make more conscious choices for environmental improvement. Additional training modules should highlight the ripple effects of participant contributions and provide concrete ways for citizens to contribute to landscape recovery from their homes. This approach would help convert generalized climate anxiety into practical engagement, empowering



participants with accessible 'micro-actions' that collectively advance nature recovery goals while reinforcing the personal impact of their involvement.

- 5.2.4 Working across diverse landscapes from coastal zones to upland moors, citizen participants have mapped habitats at unprecedented scale and pace while experiencing profound shifts in their connection to nature. These compelling results should be leveraged to advocate for policy changes that formally recognise Earth Observation citizen science as a legitimate methodology within environmental monitoring frameworks. Communications should emphasise how this approach bridges professional conservation priorities with meaningful public participation in nature recovery, creating a powerful pathway for inclusive, sustainable landscape transformation.

6 BIBLIOGRAPHY

Pateman, R., Dyke, A., West, S. 2021. The Diversity of Participants in Environmental Citizen Science, *Citizen Science: Theory and Practice*, 6(1), 9. *Citizen Science: Theory and Practice*, 6(1), 9. <https://doi.org/10.5334/cstp.369>



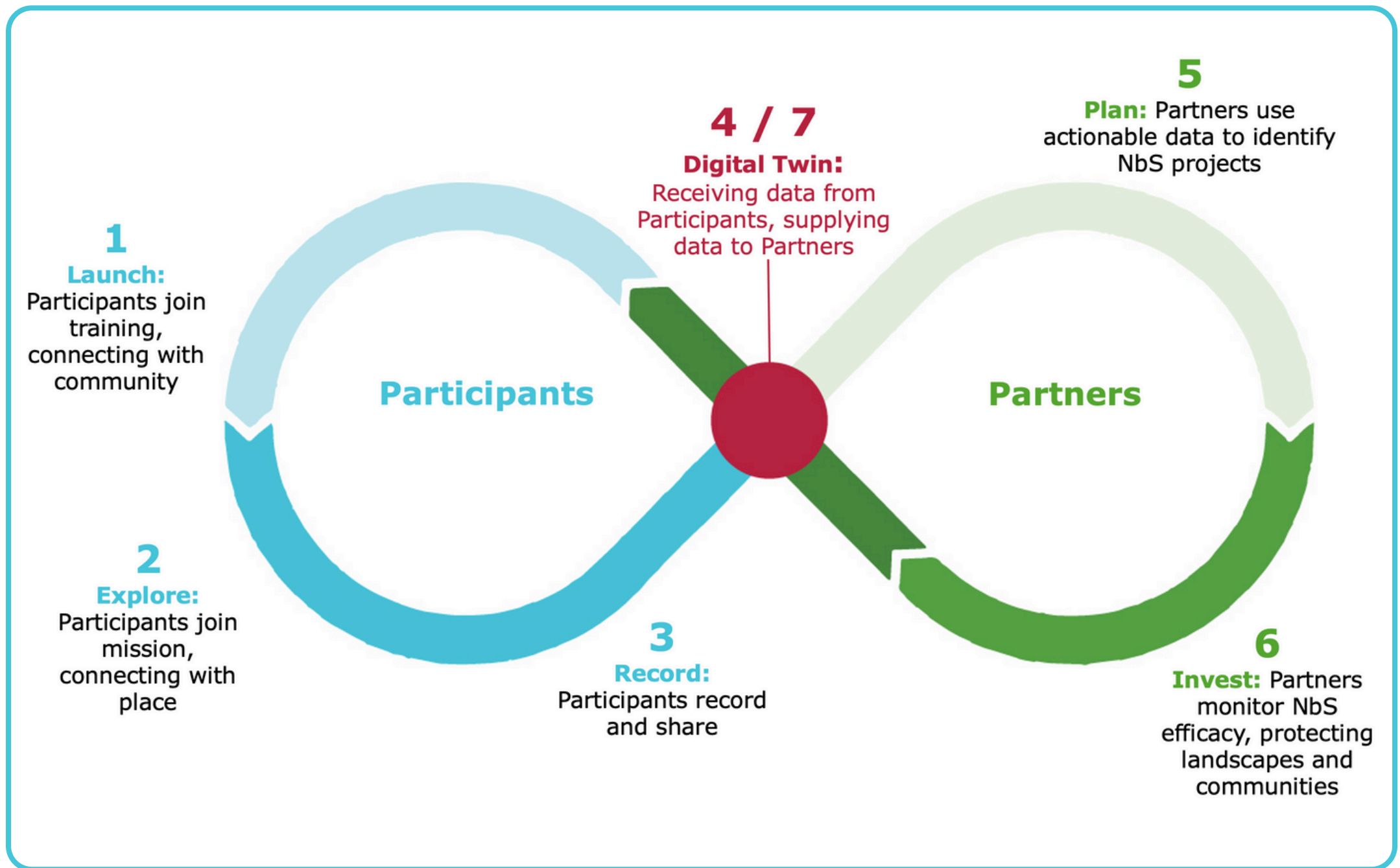
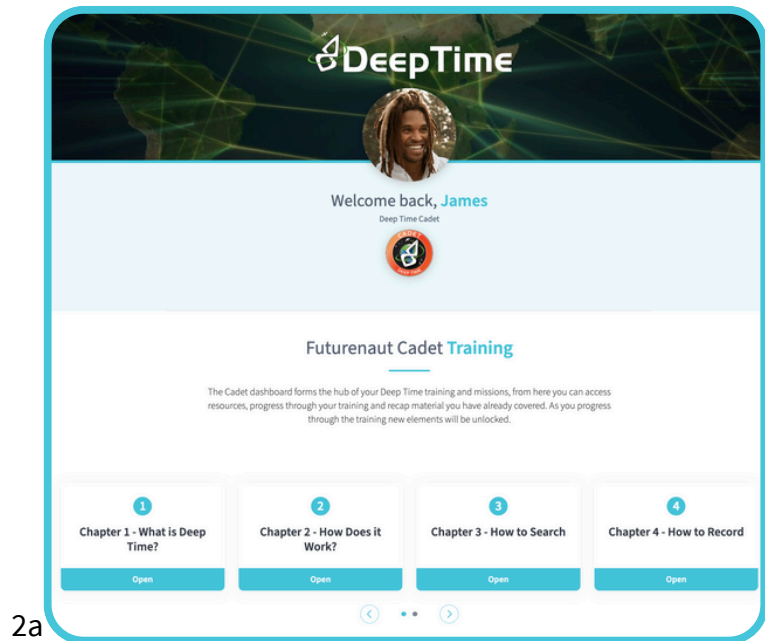
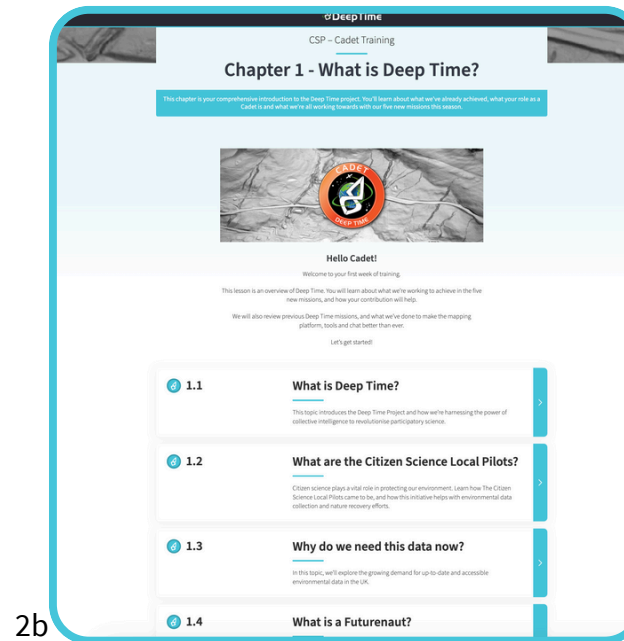


Figure 1 - The Deep Time High Level Workflow



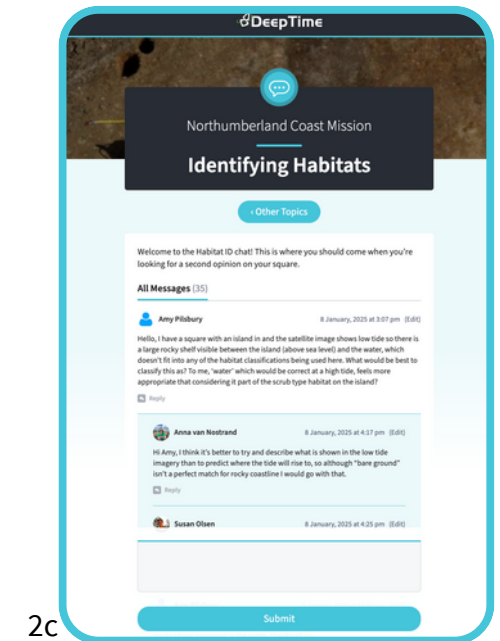
2a

The participant training dashboard



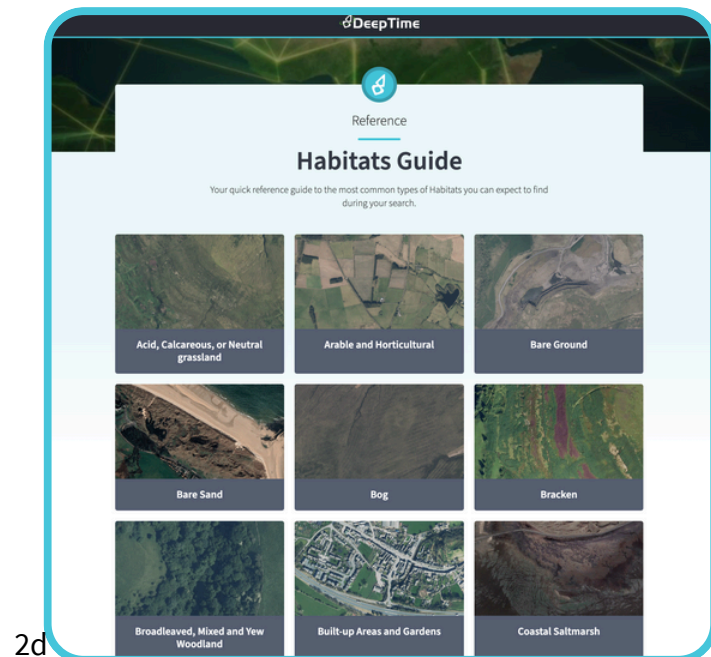
2b

The Deep Time training course



2c

The mission chat



2d

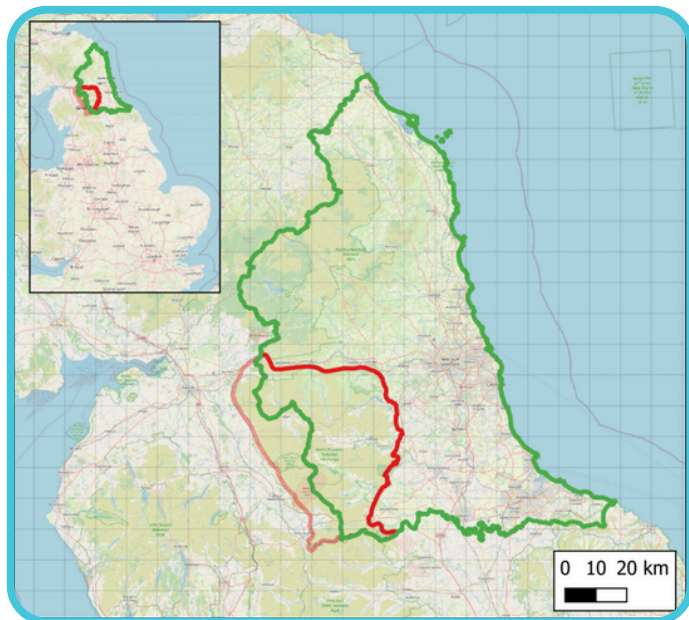
The Habitat Guide



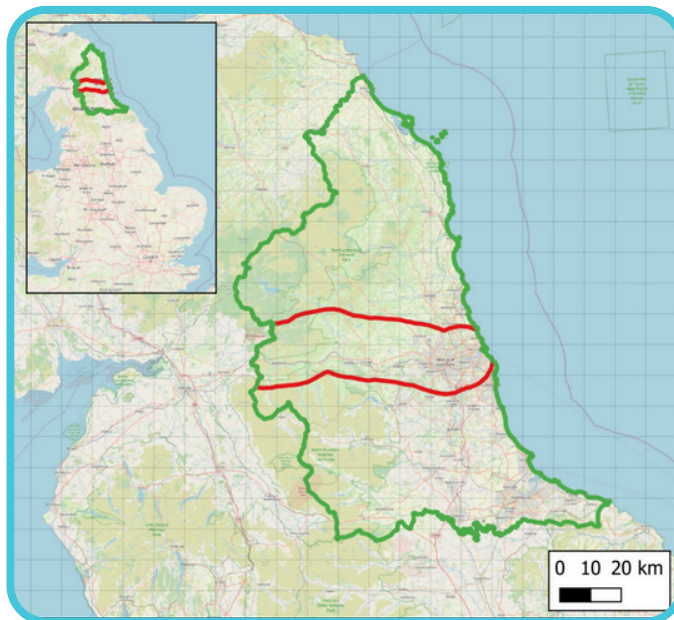
2e

The Deep Time mapping portal

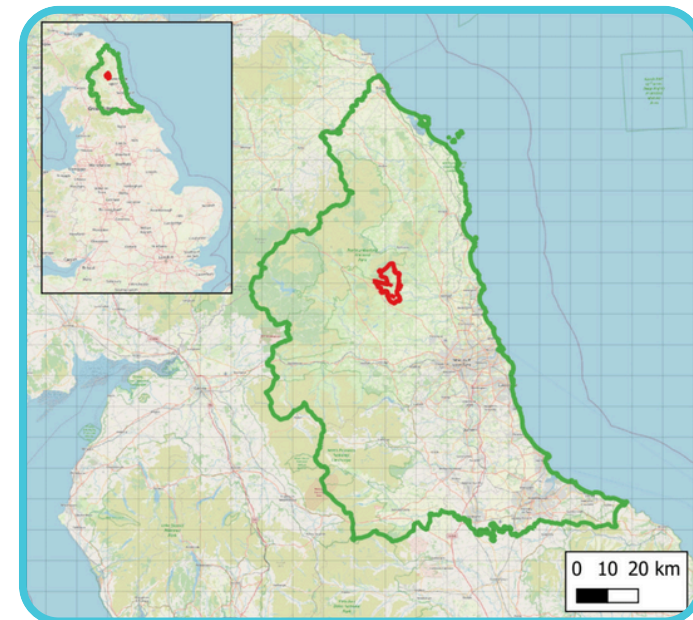
Figure 2 - The Deep Time platform and training materials



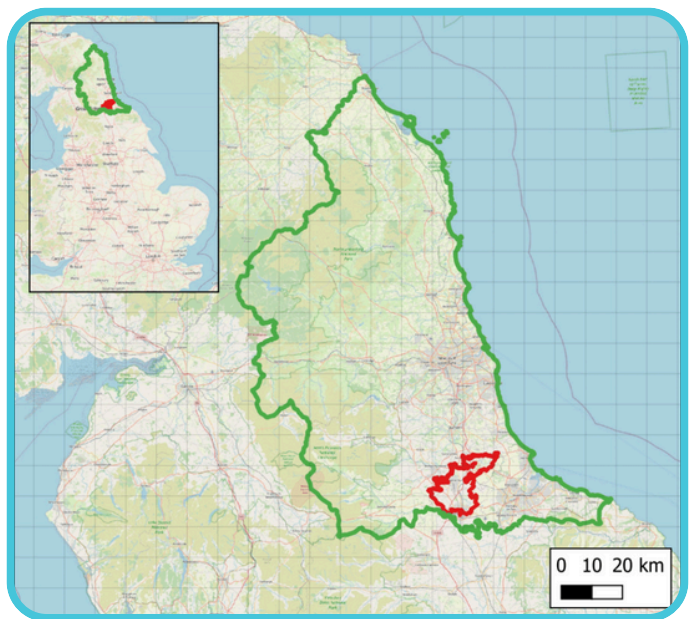
North Pennines National Landscape



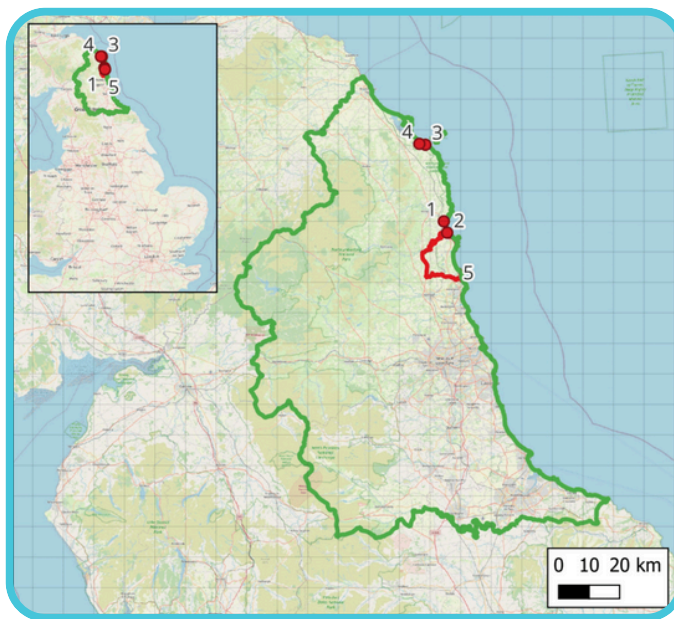
Hadrian's Wall Corridor



Wallington Estate



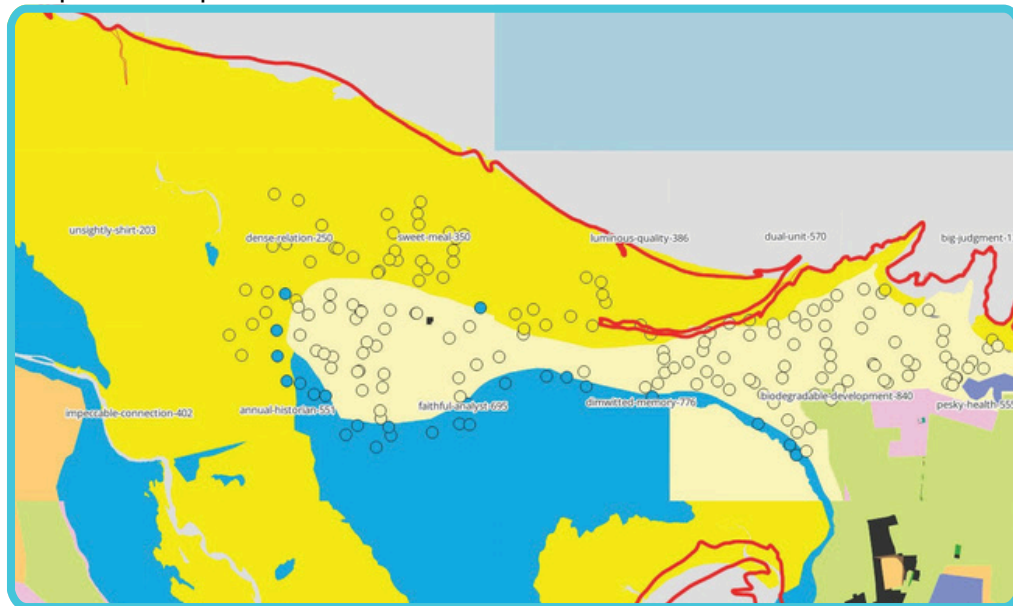
Brightwater Landscape



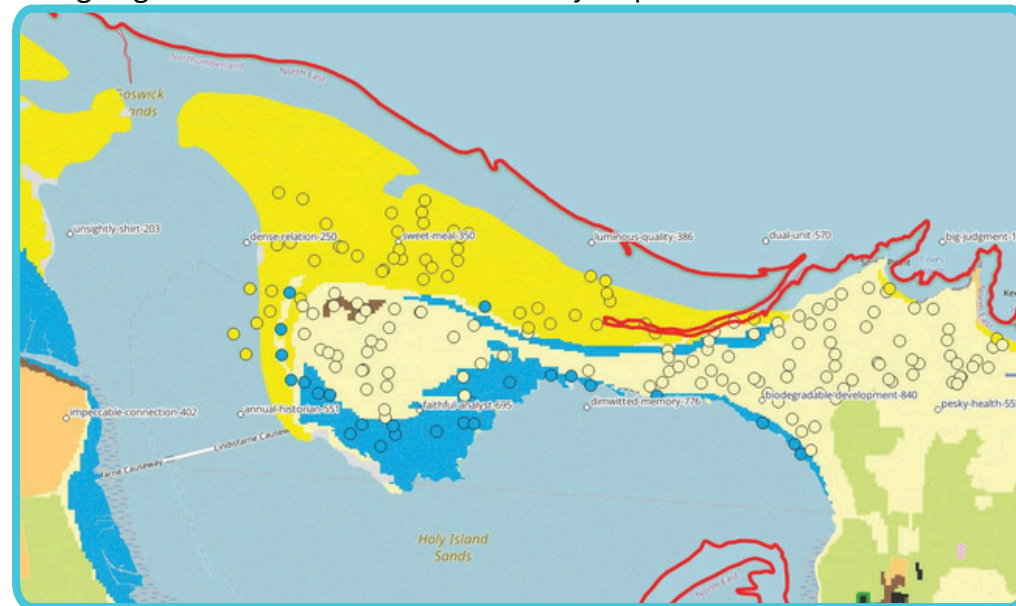
Northumberland Coast National Landscape

Figure 3 - Location of the CSLP project areas within Northumbria

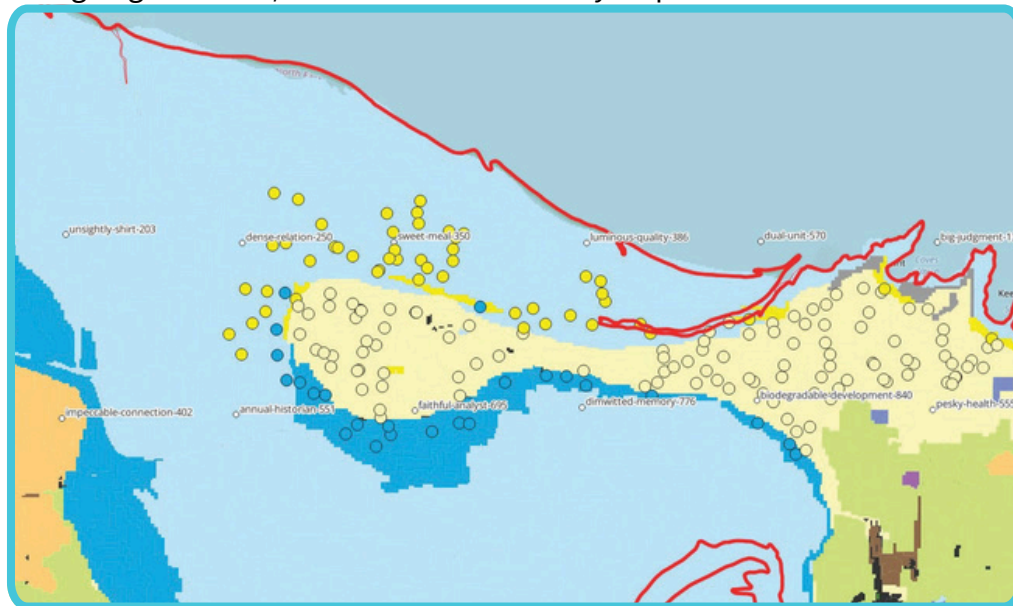
Deep Time map data



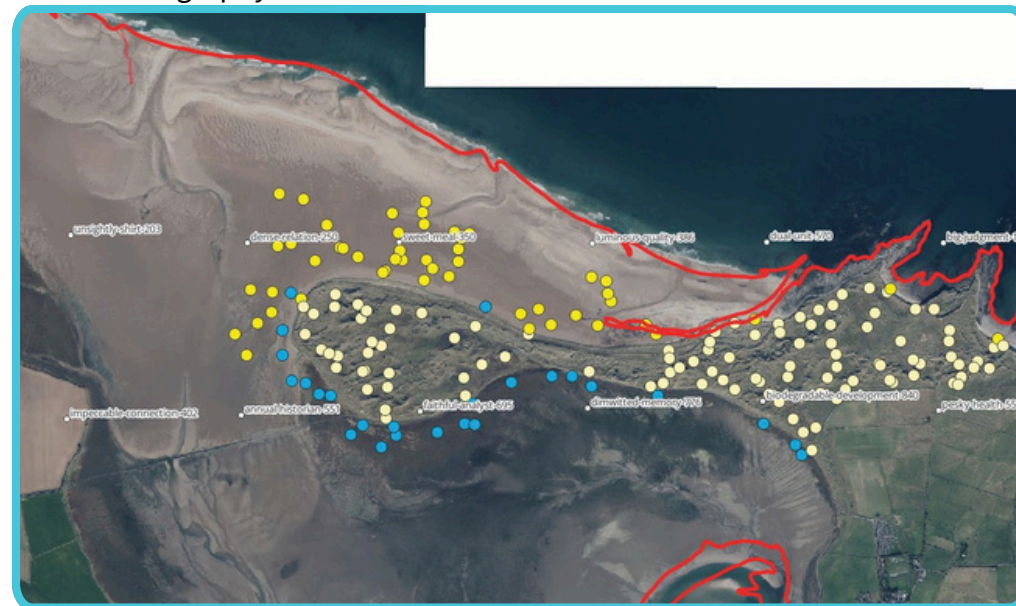
Living England Phase IV Habitat Probability Map



Living England 2022/2023 Habitat Probability Map



Aerial Photography of Great Britain 25cm



This imagery represents Deep Time 12 grids in the Northumberland Coast National Landscape study area where there are 201 Living England ground survey points

Figure 4 - Example of dataset comparison for the Living England ground survey point QA process

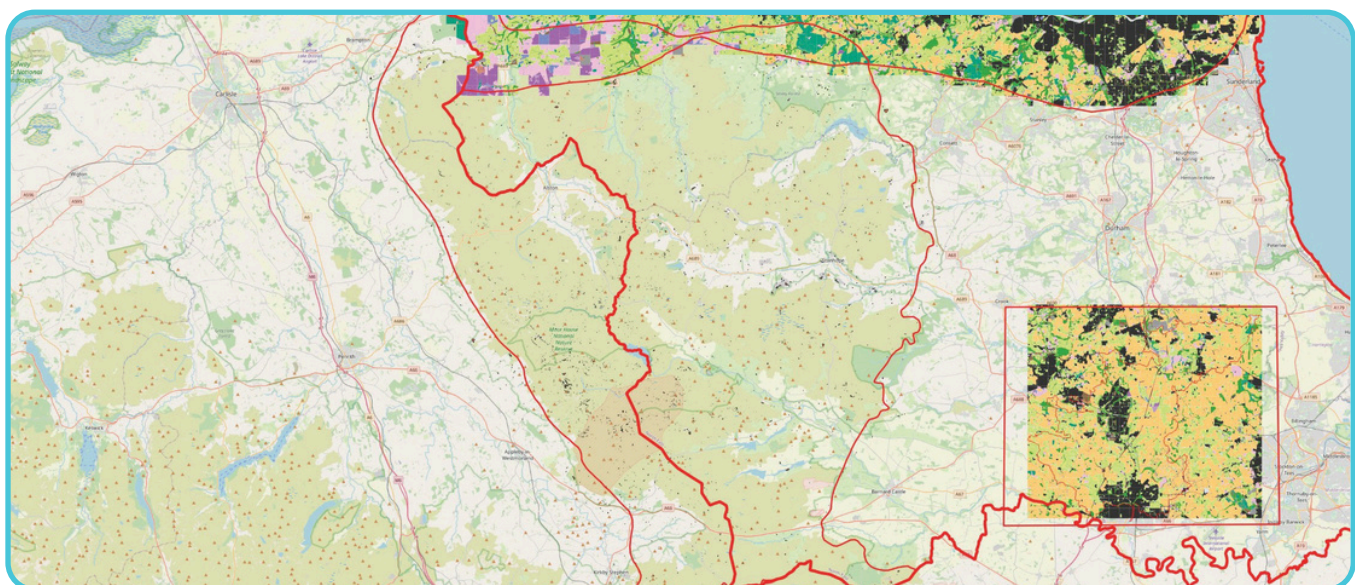
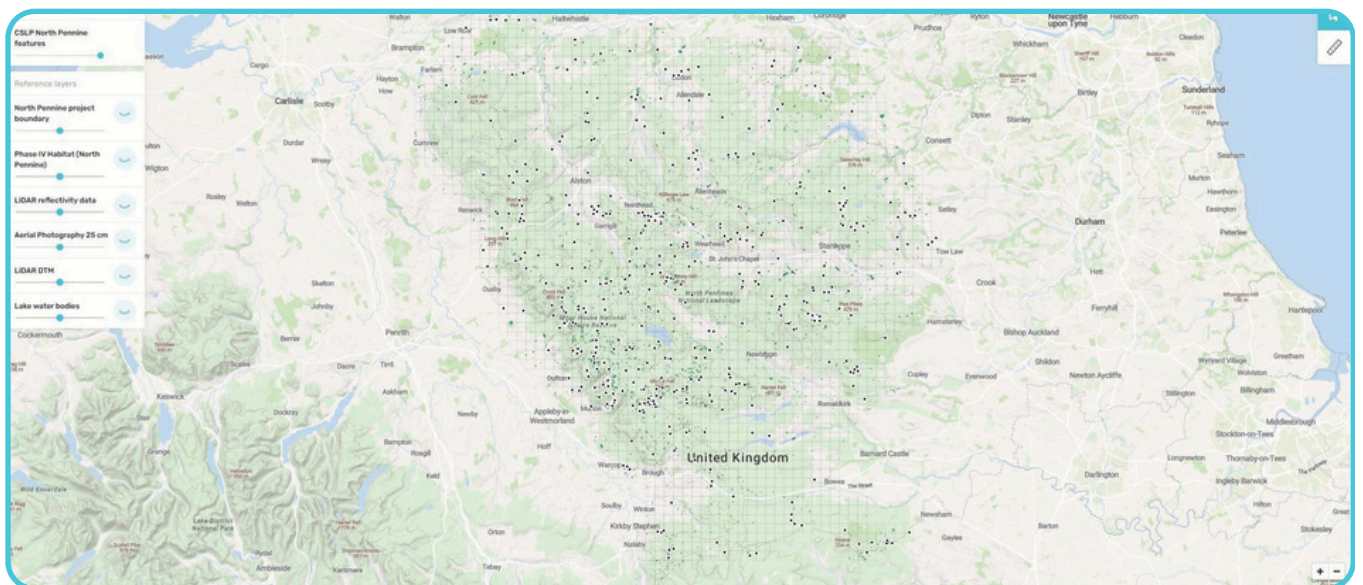
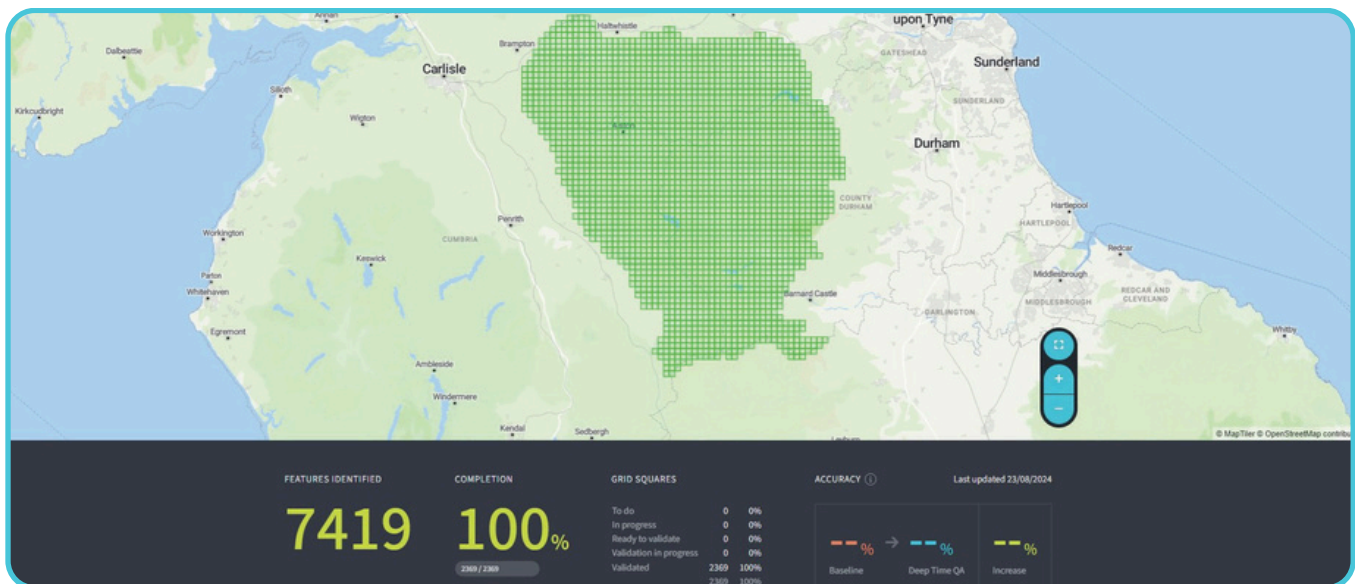
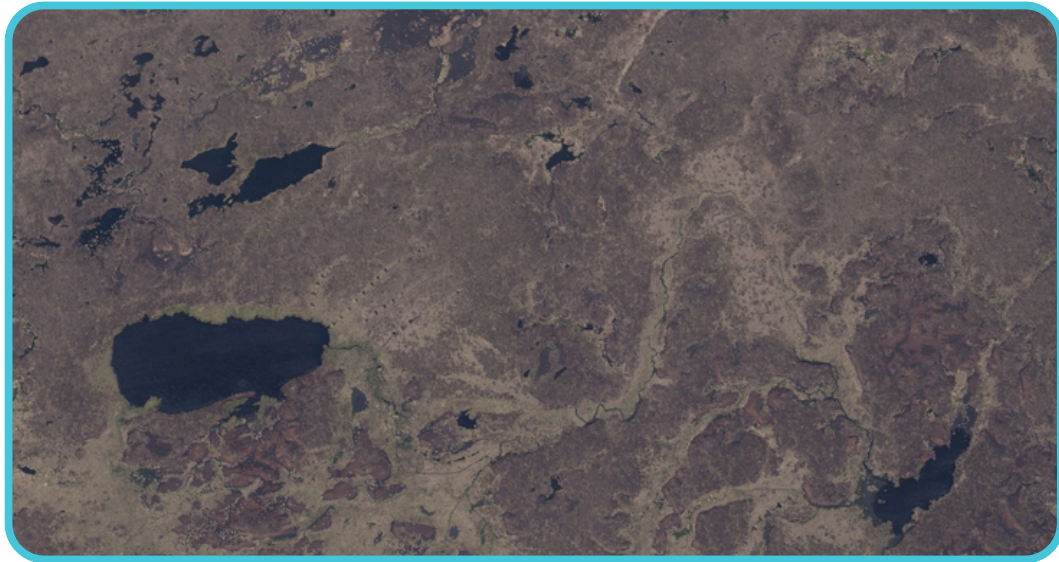
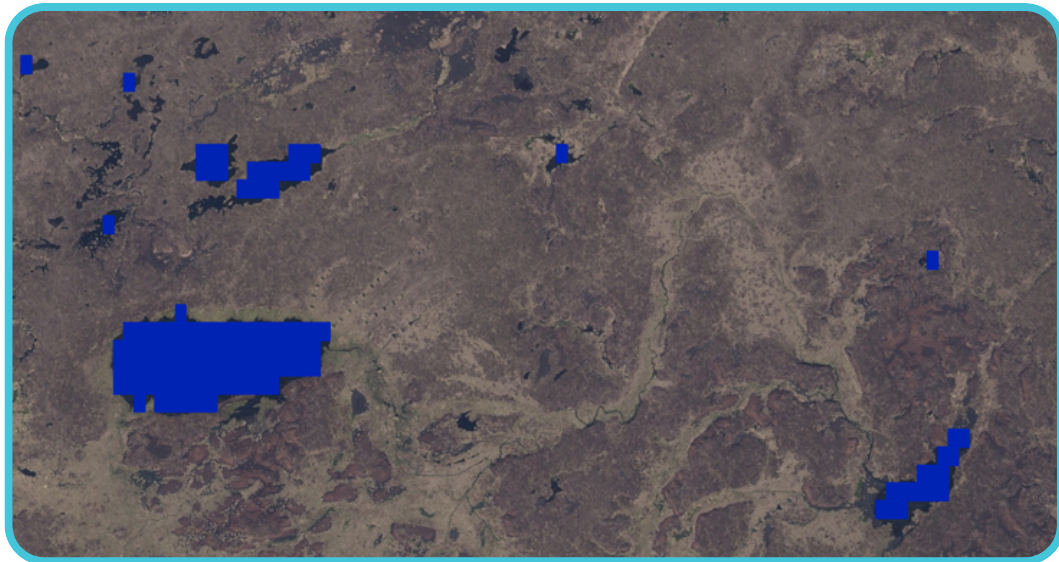


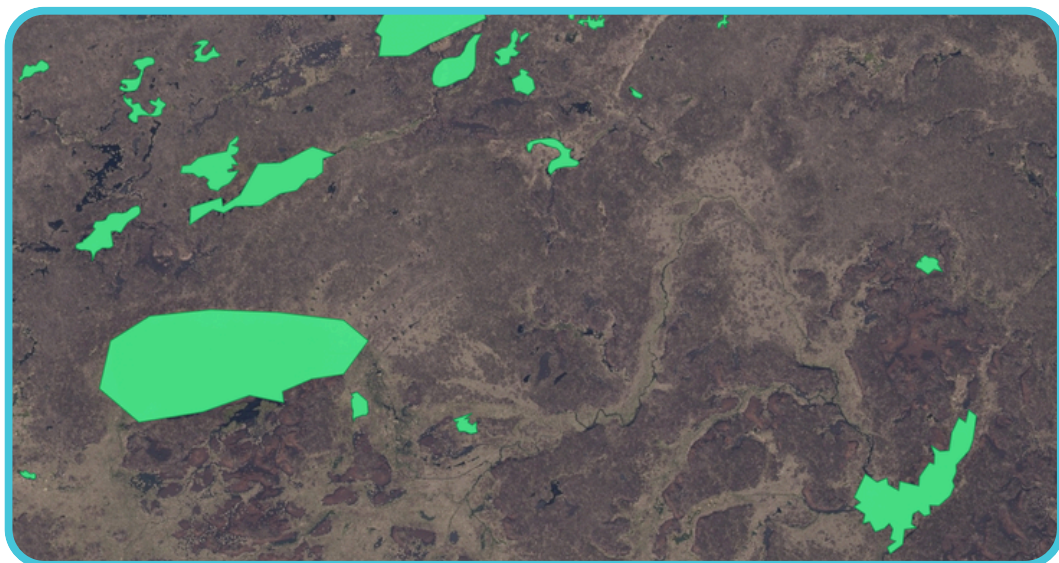
Figure 5 - The North Pennines National Landscape mission overview



Aerial Photography of Great Britain 25cm



Polygons derived through LiDAR reflectivity data



Deep Time CSLP polygons

Figure 6 - Comparison of Deep Time dataset compared to the polygons created using LiDAR reflectivity

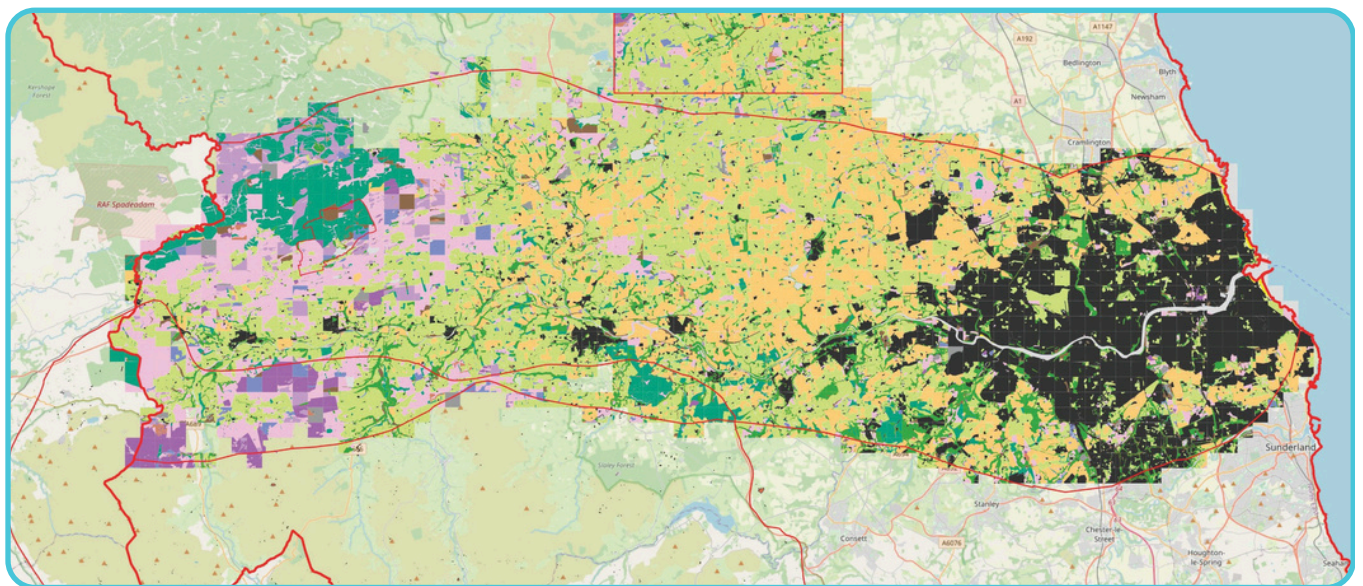
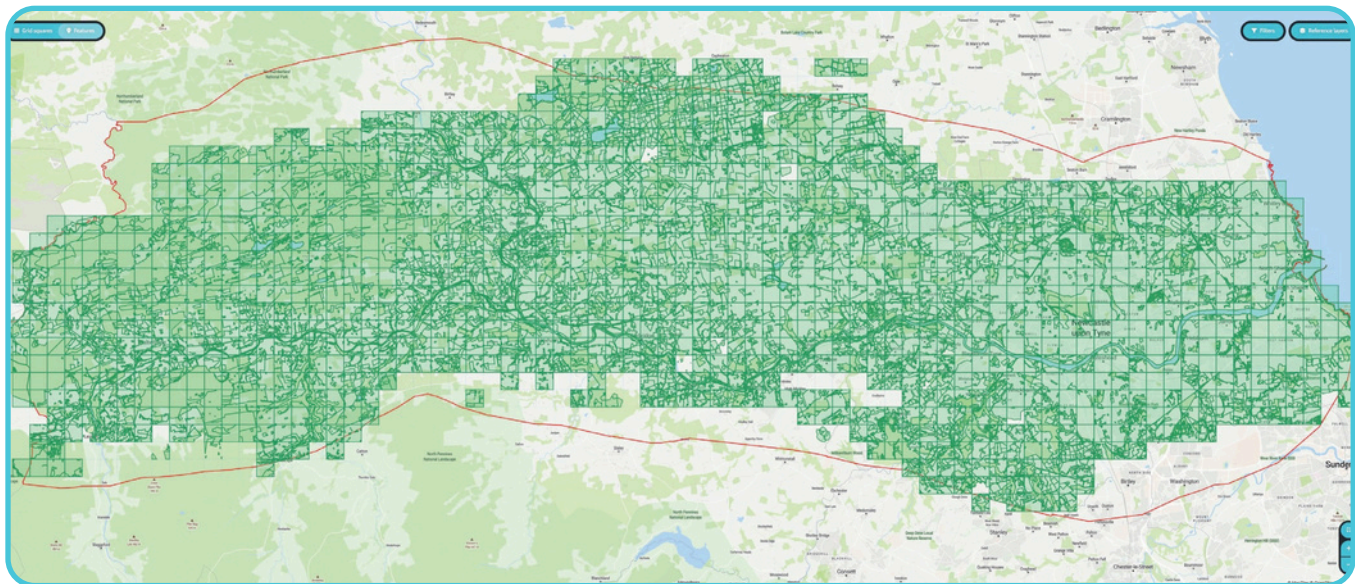
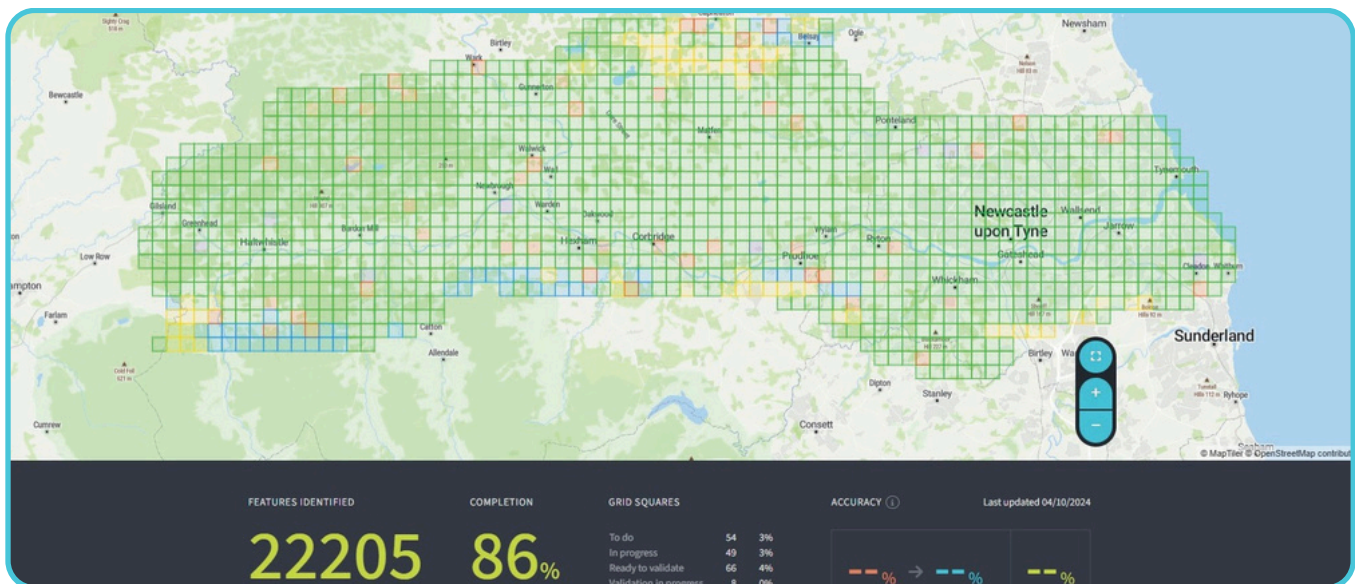


Figure 7 - The Hadrian's Wall mission overview

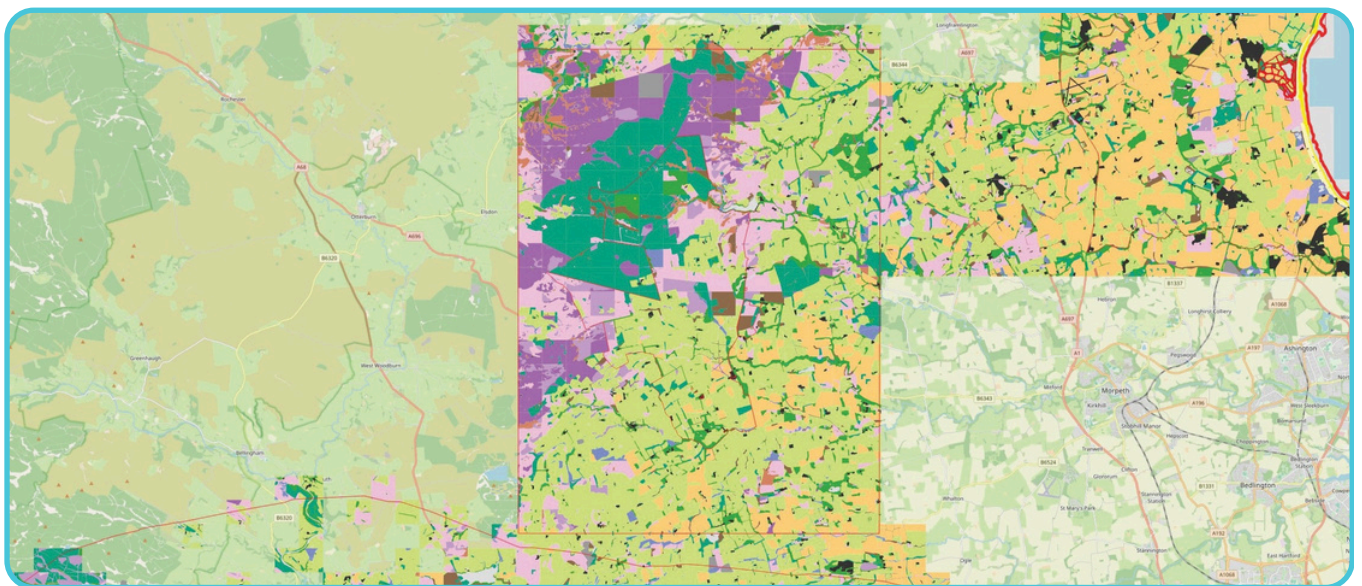
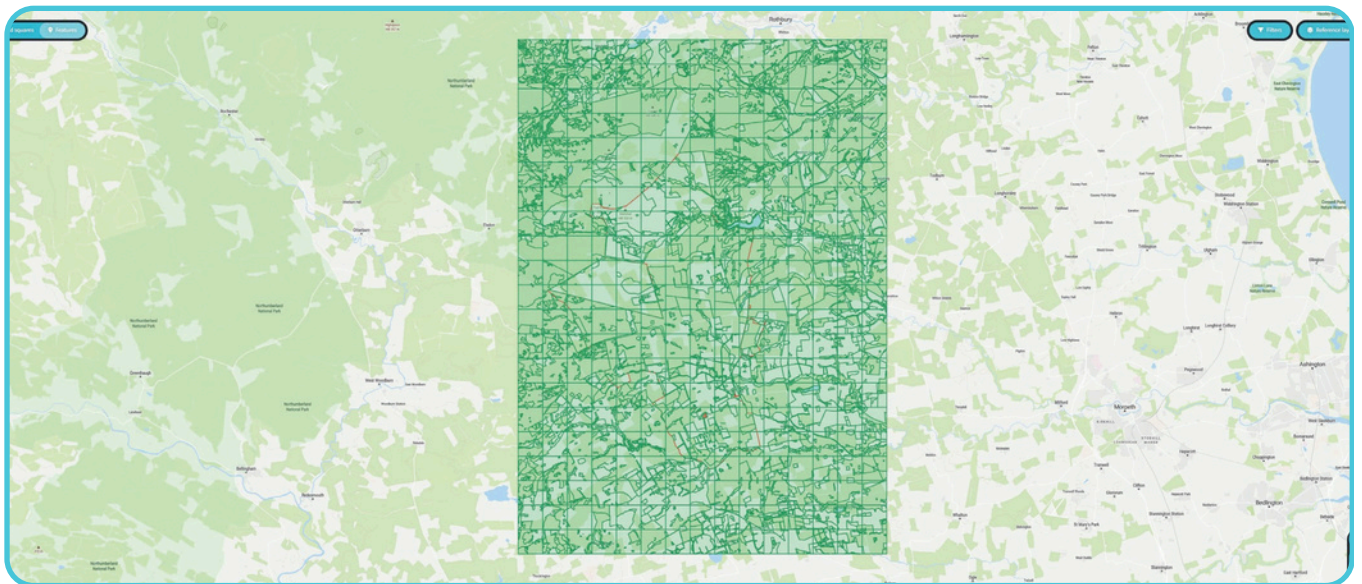
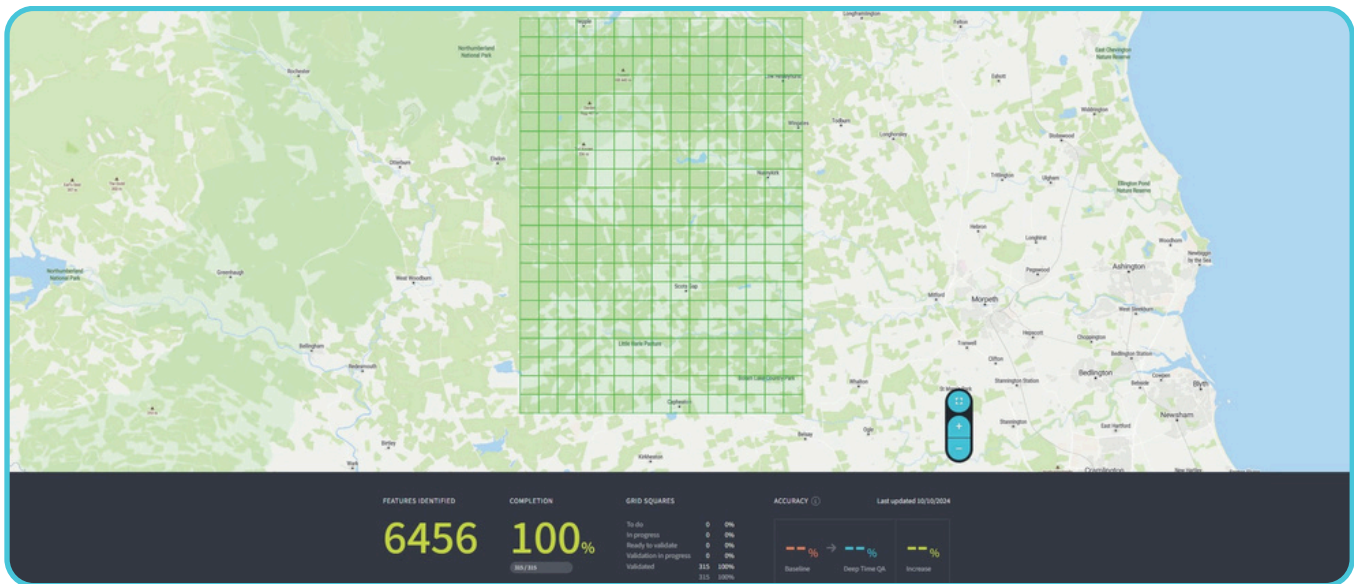


Figure 8 - The Wallington Estate mission overview

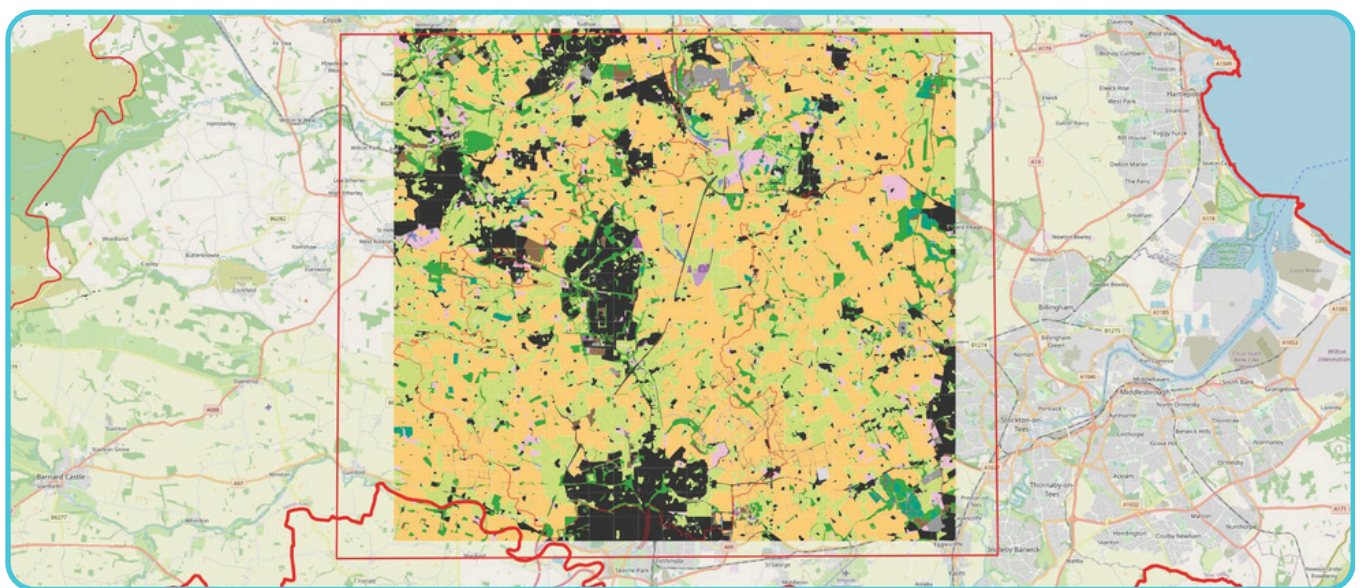
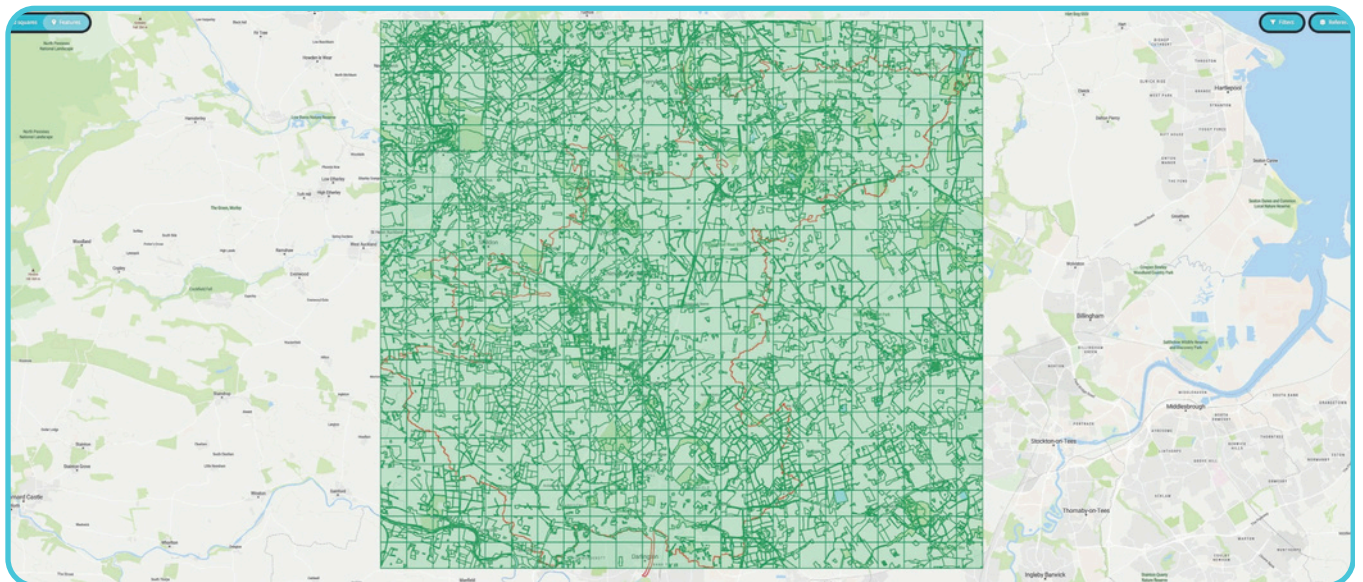
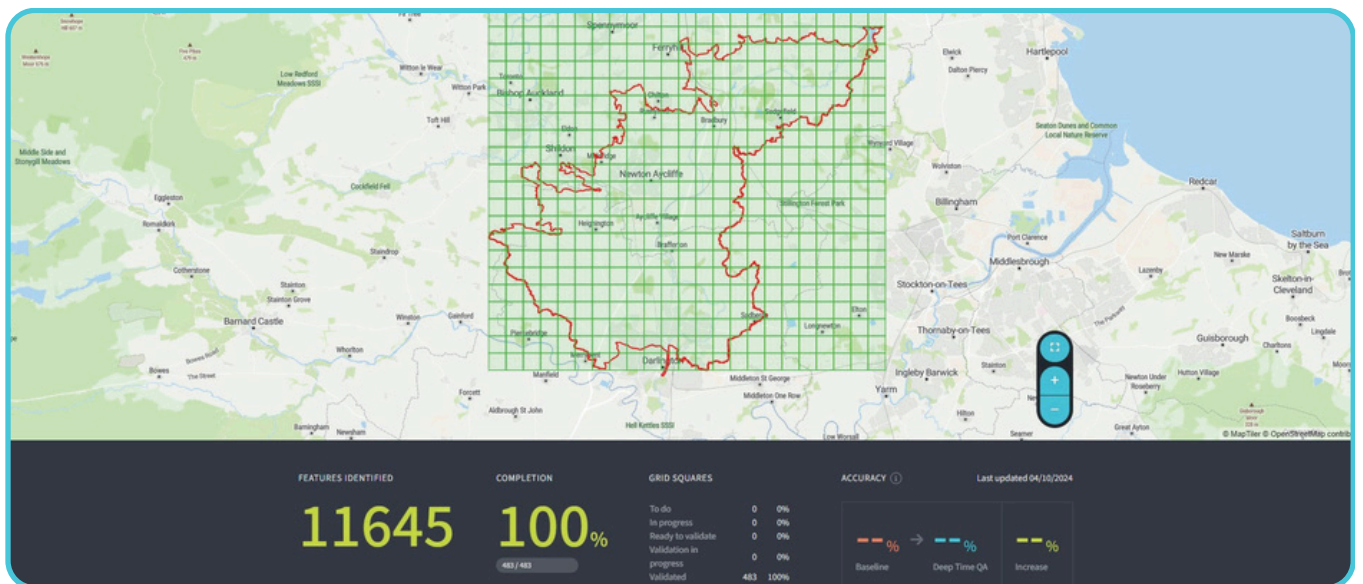


Figure 9 - The Brightwater mission overview

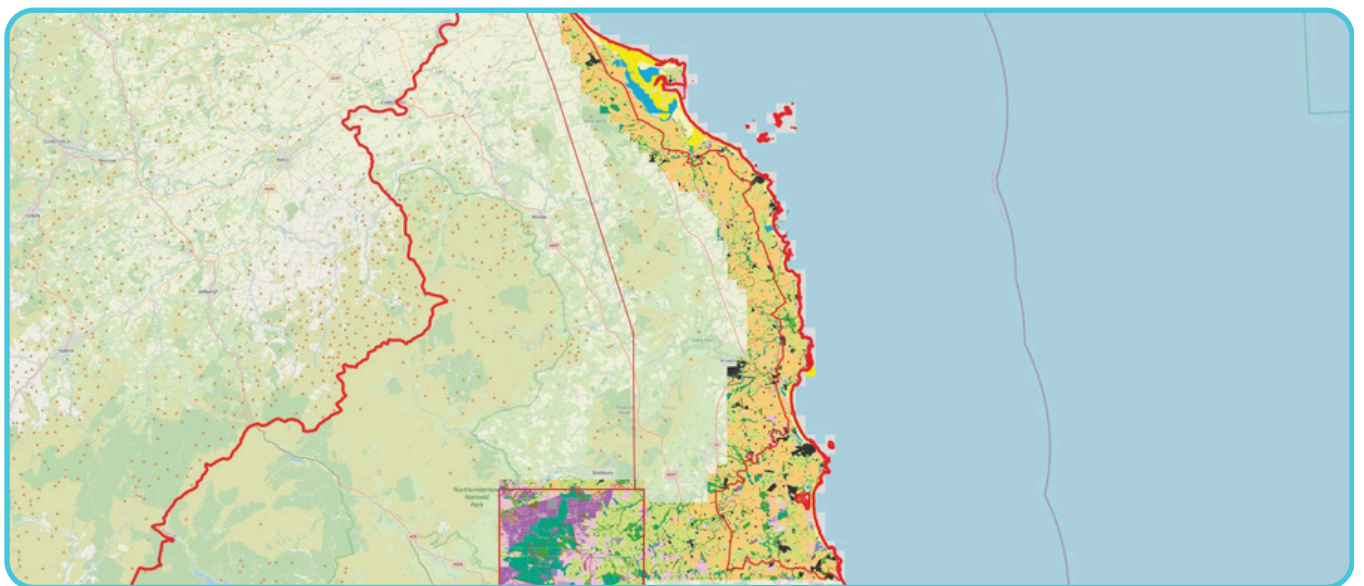
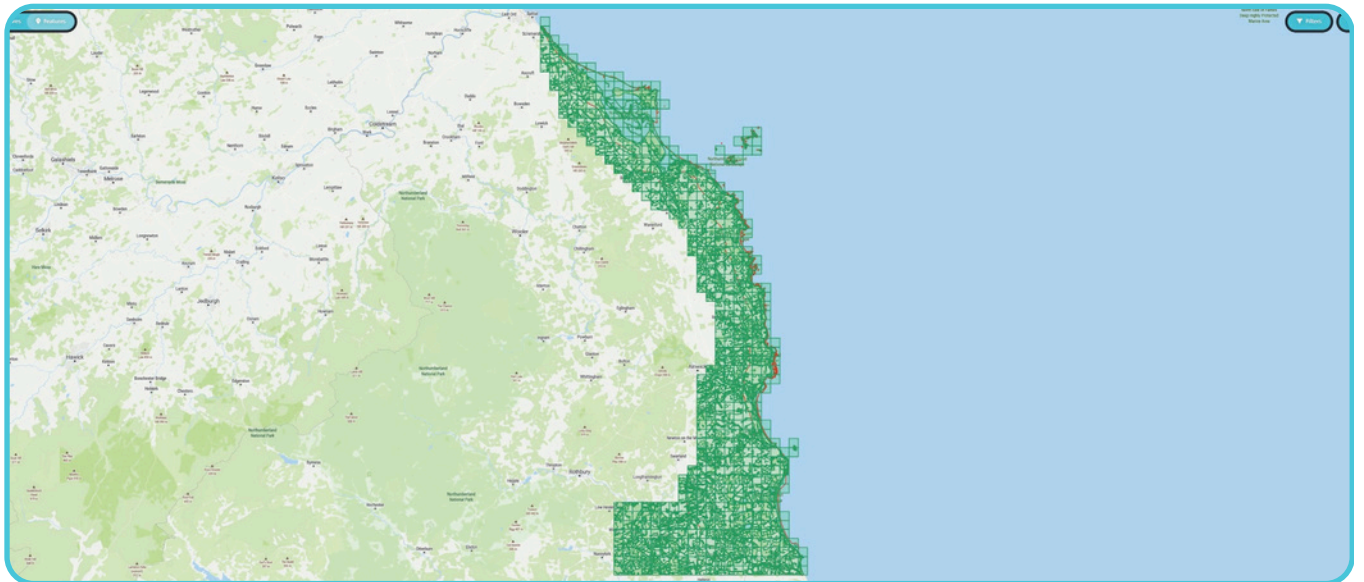
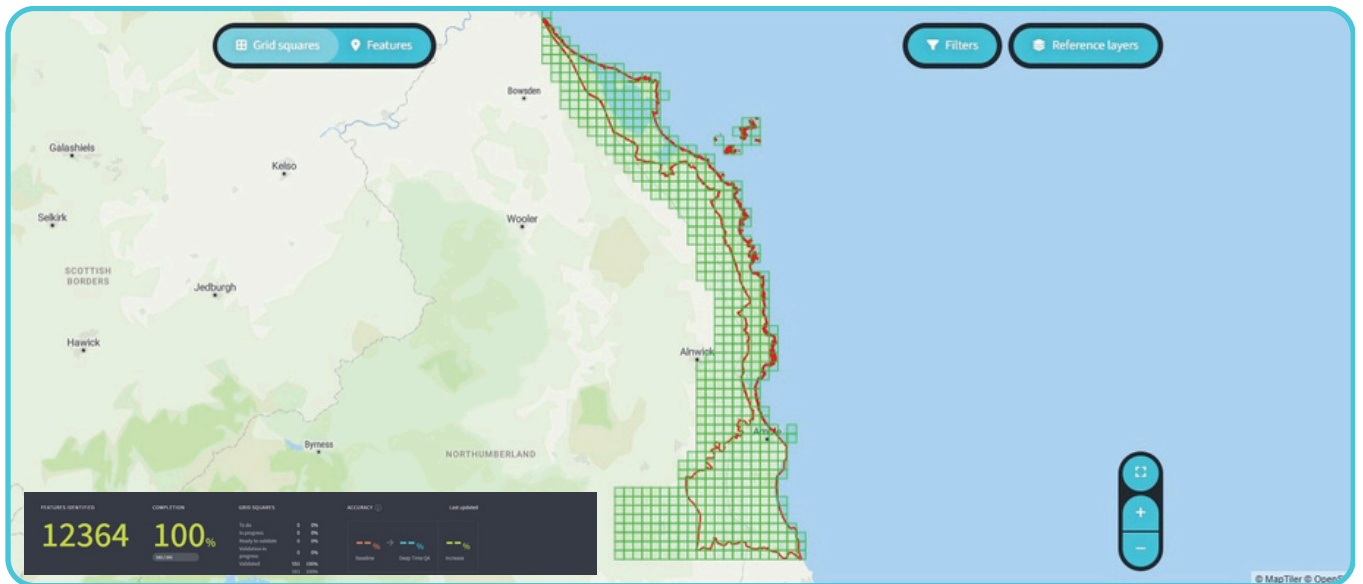


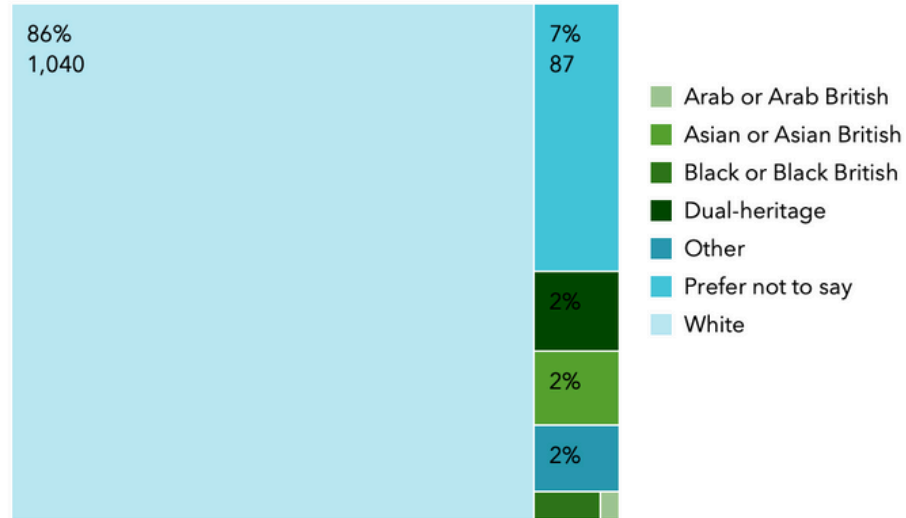
Figure 10 - The Northumberland Coast National Landscape mission overview



Figure 11- Participant country of residence

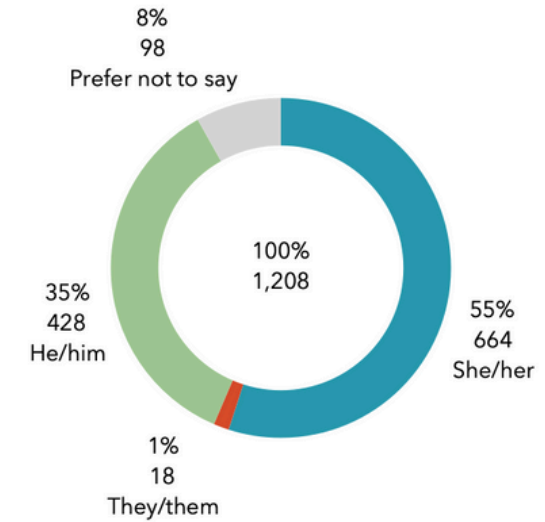
12a

Ethnicity



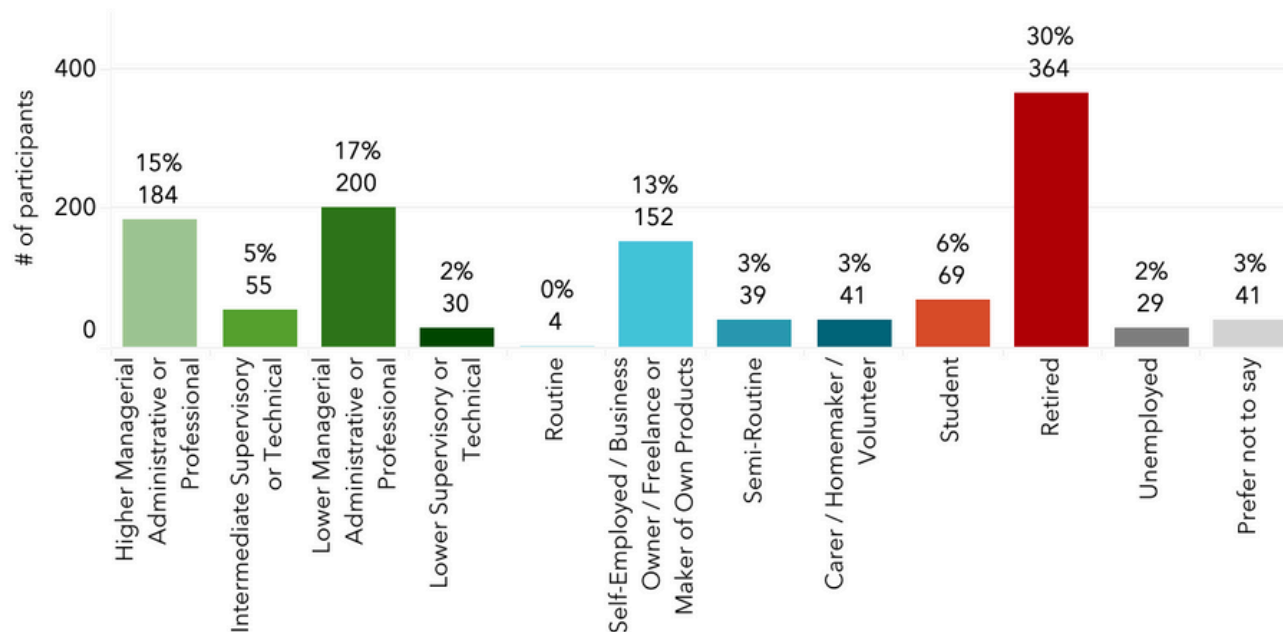
12b

Preferred pronouns



12c

Occupation



12d

Age

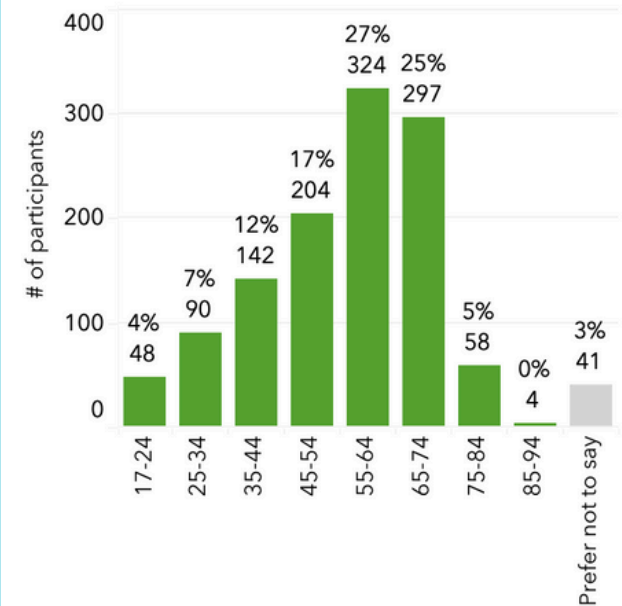


Figure 12 - Participant socioeconomic data

Have you previously participated in a similar project?

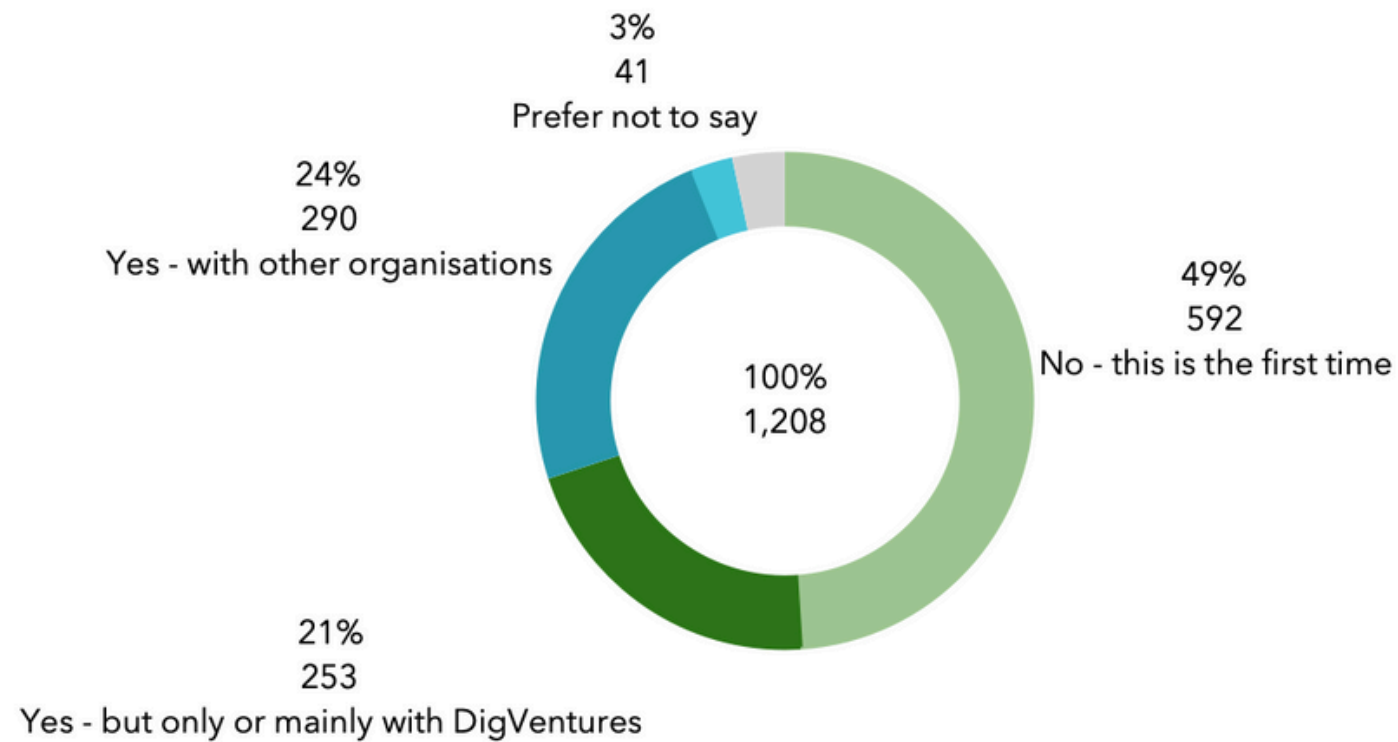
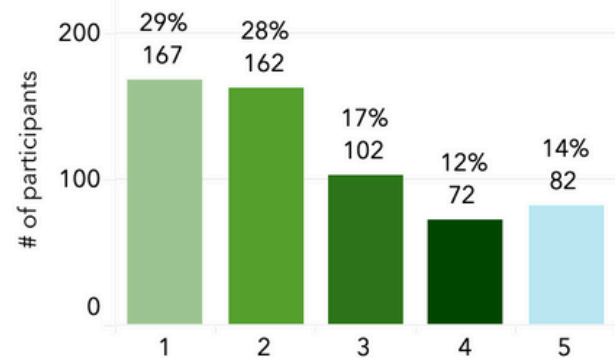


Figure 13 - Participant previous experience

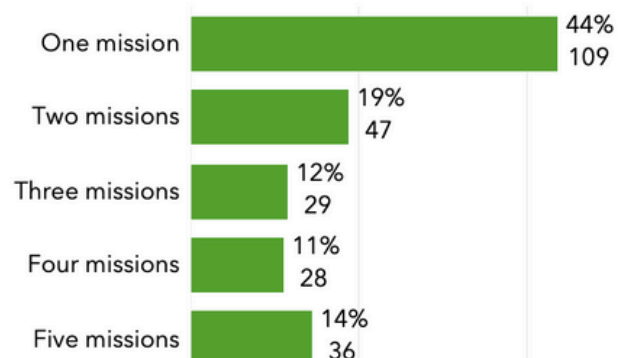
14a

Number of participants per mission



14b

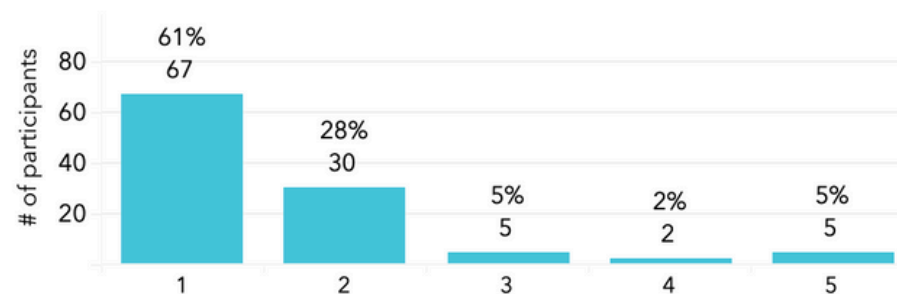
Number of missions



- 1 - North Pennines National Landscape
- 2 - Hadrian's Wall Corridor
- 3 - Wallington Estate
- 4 - Brightwater Landscape
- 5 - Northumberland Coast National Landscape

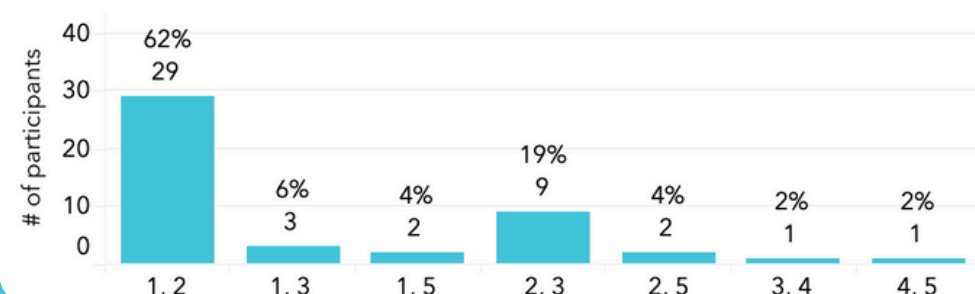
14c

Single mission participants



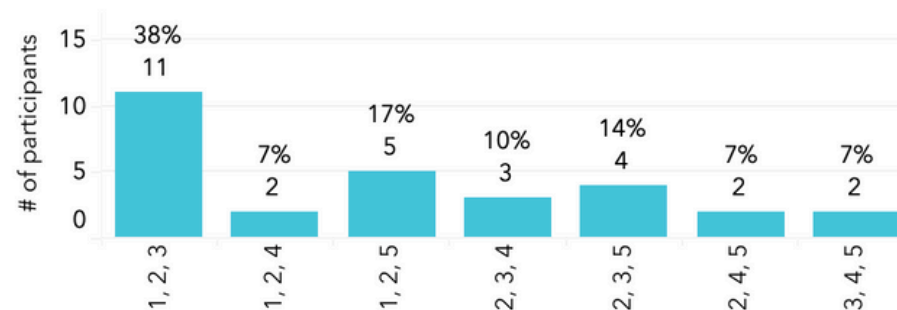
14d

Participants in two missions



14e

Participants in three missions



14f

Participants in four missions

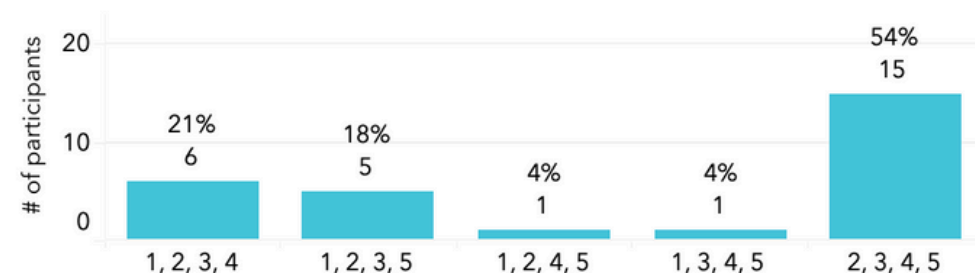
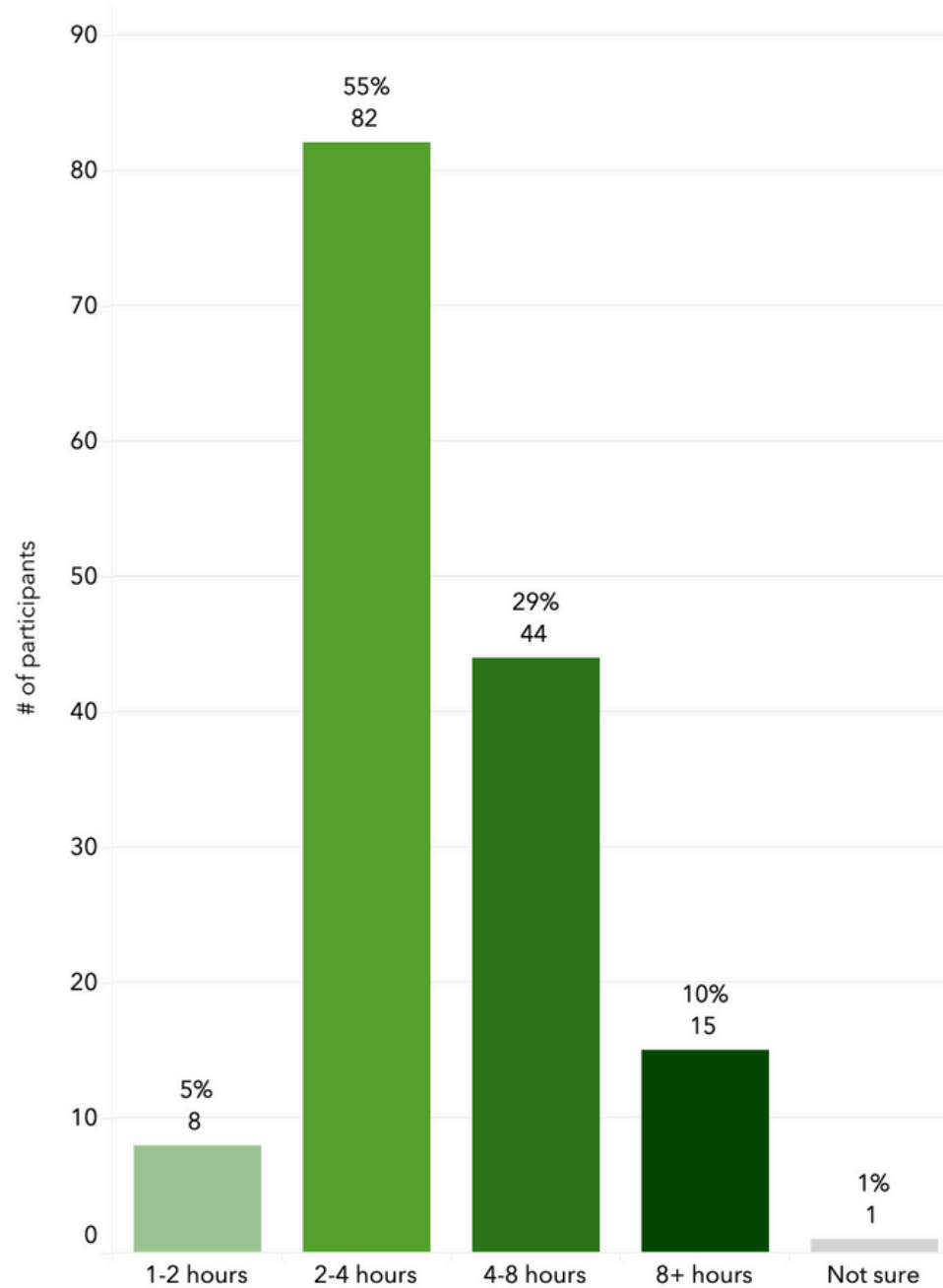


Figure 14 - Mission Participation

Predicted hours of availability



Self assessed weekly hours spent on the platform

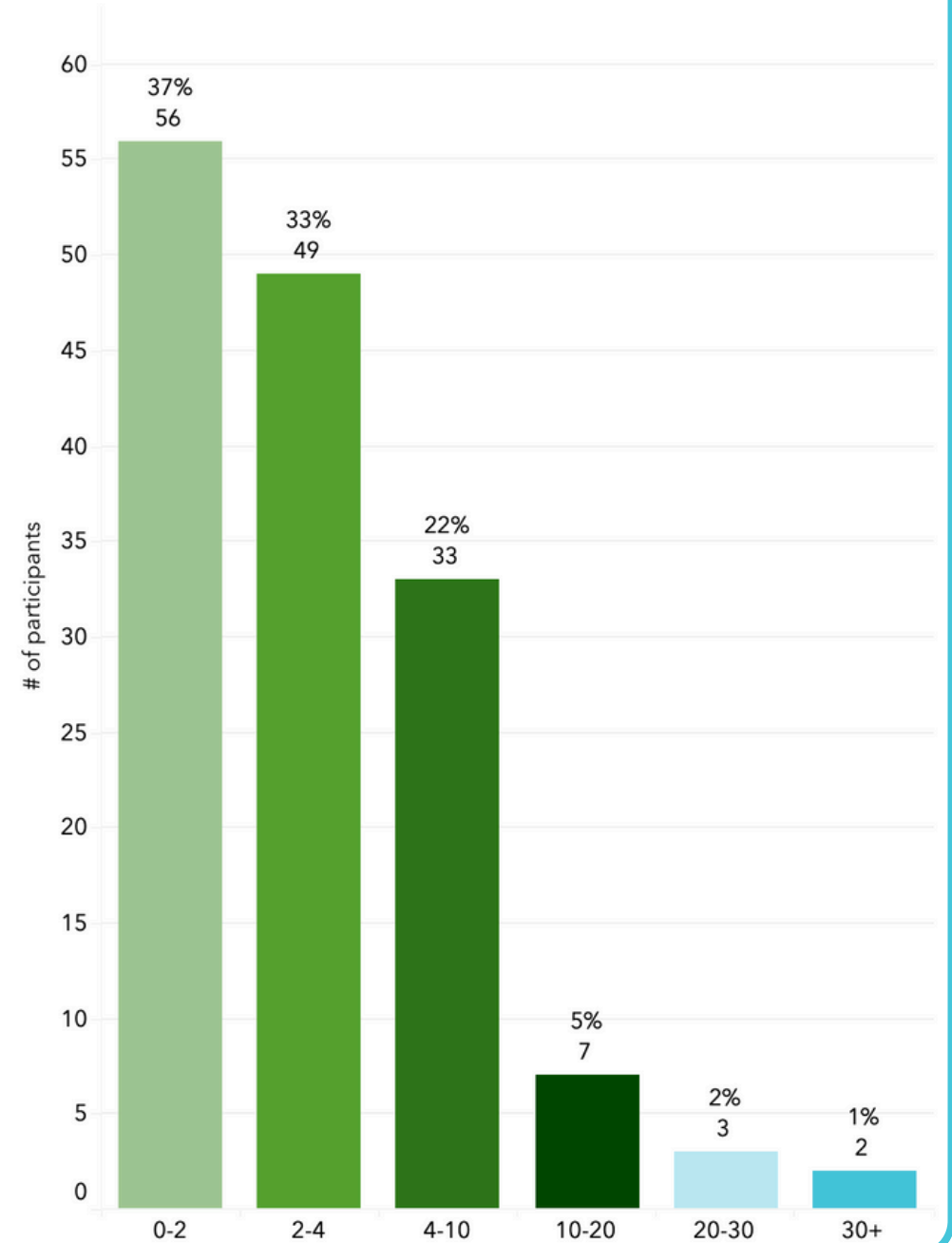


Figure 15 - Hours contributed

Why did you want to join this project?

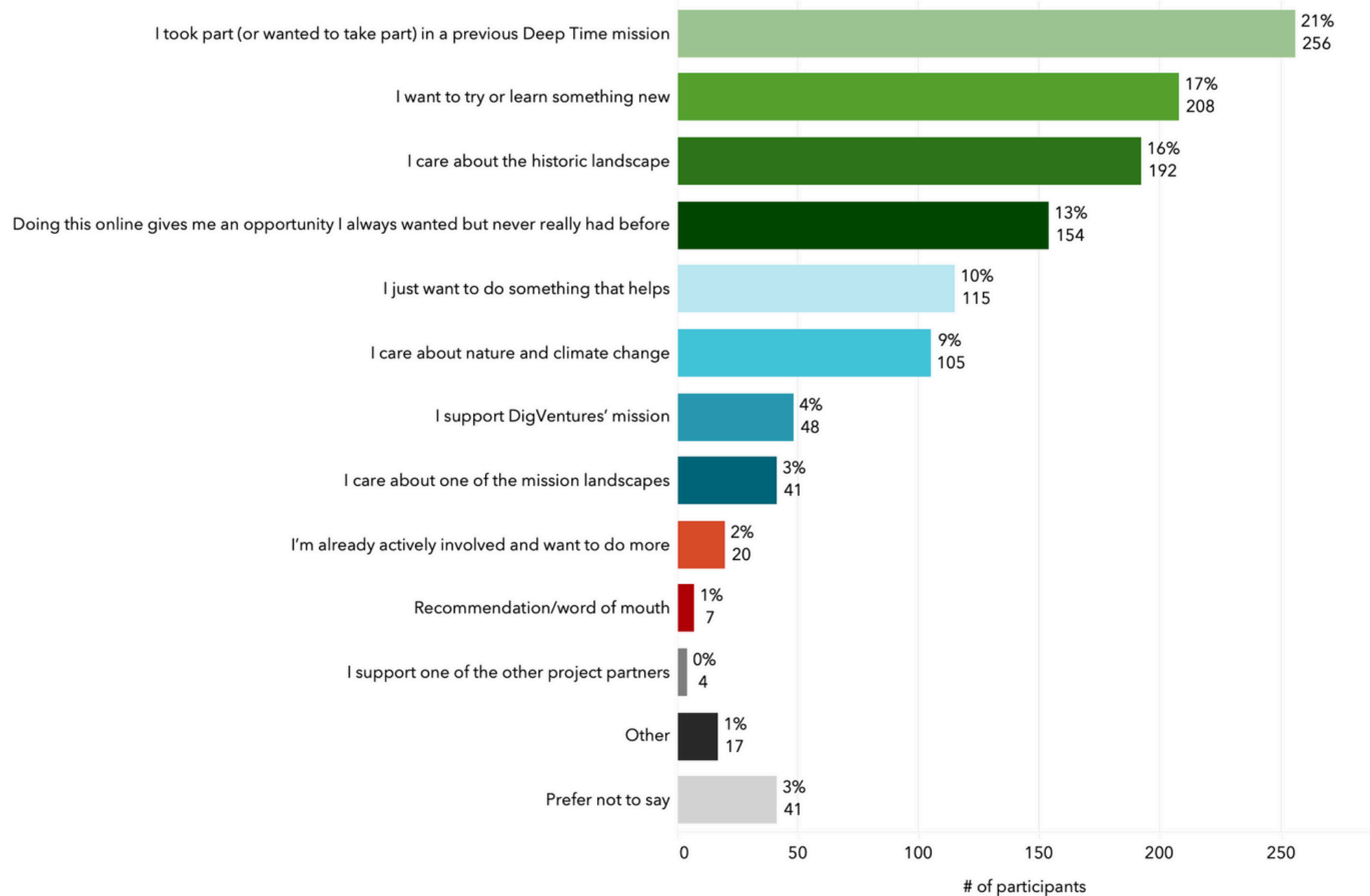
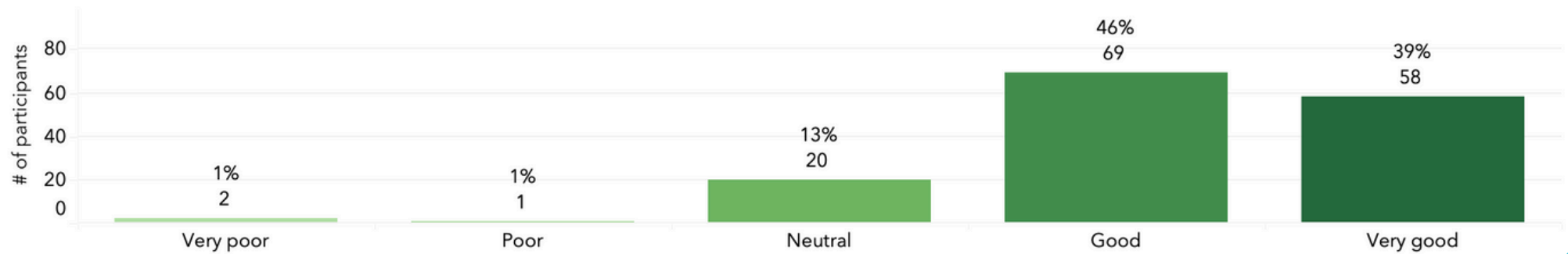


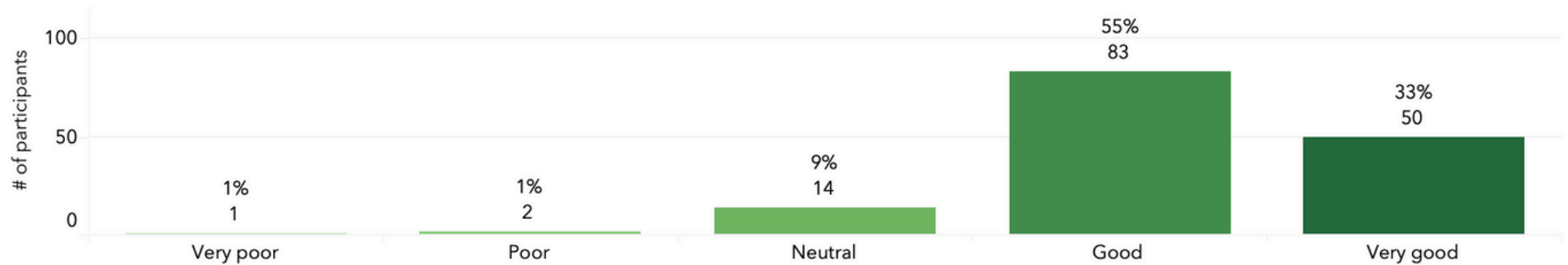
Figure 16 - Motivation for joining

How do you rate Deep Time as a way to learn new skills?



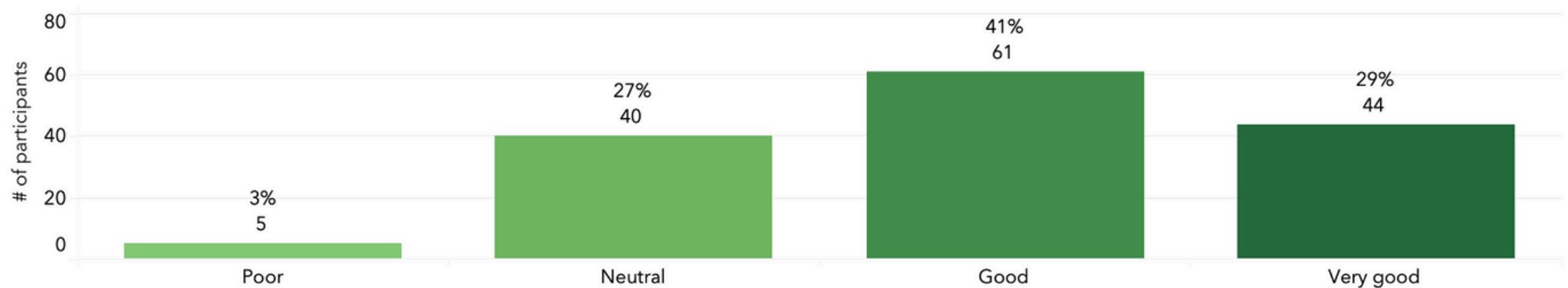
17a

How do you rate Deep Time as a way to learn more about the environment?



17b

How do you rate Deep Time as a way to get involved in nature recovery?

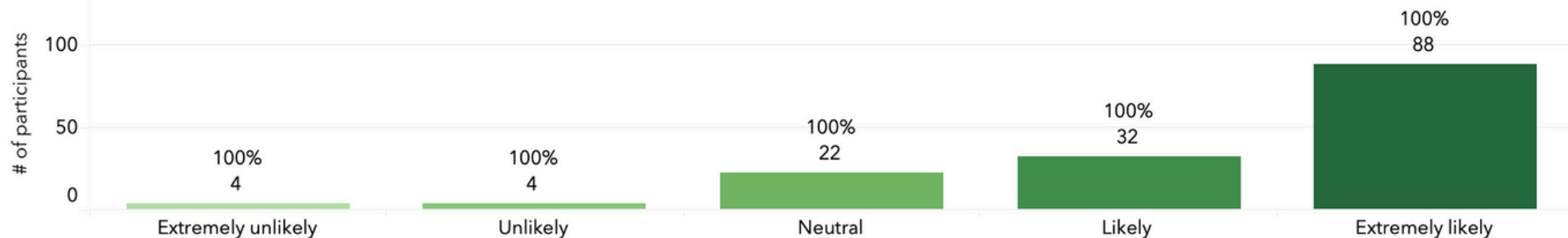


17c

Figure 17 - Participant views of value of Deep Time

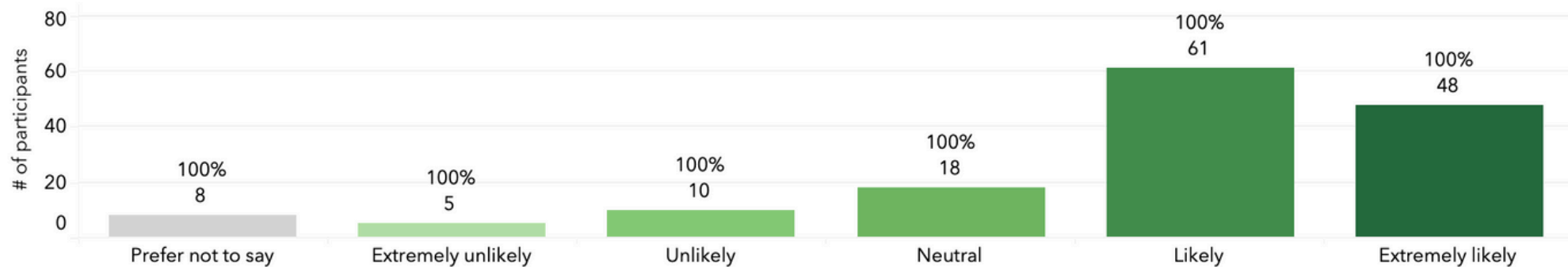
18a

How likely are you to participate in future Deep Time missions?



18b

How likely would you be to participate in future natural heritage based missions?



18c

How likely would you be to get involved in cultural heritage focussed missions?

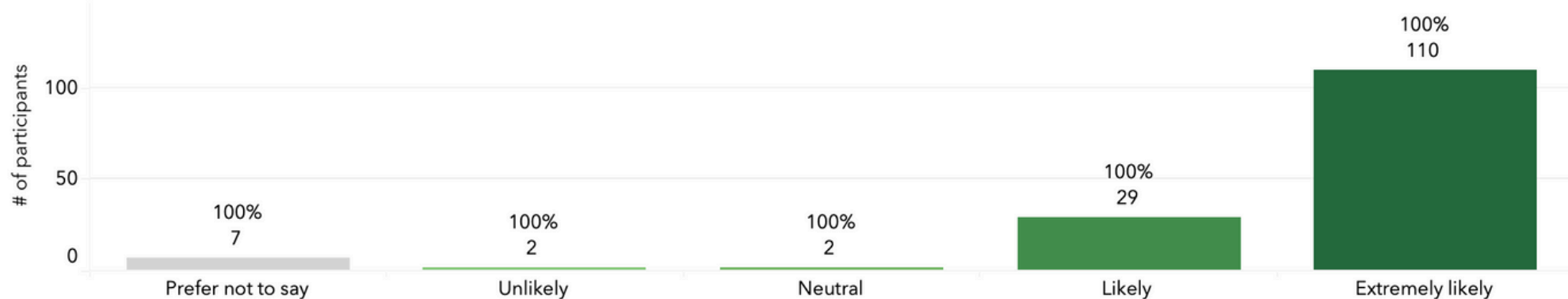
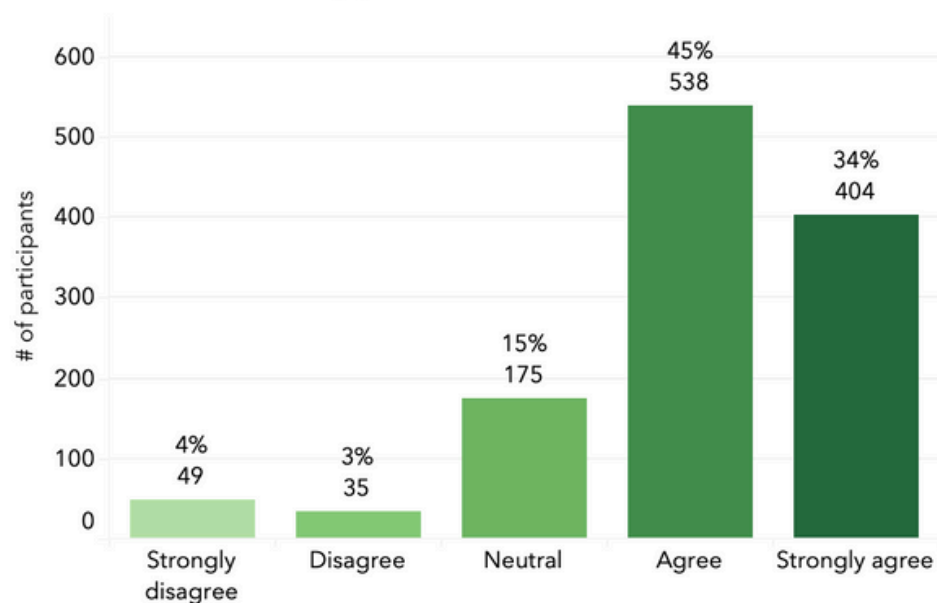


Figure 18 - Participant desire for continue contribution

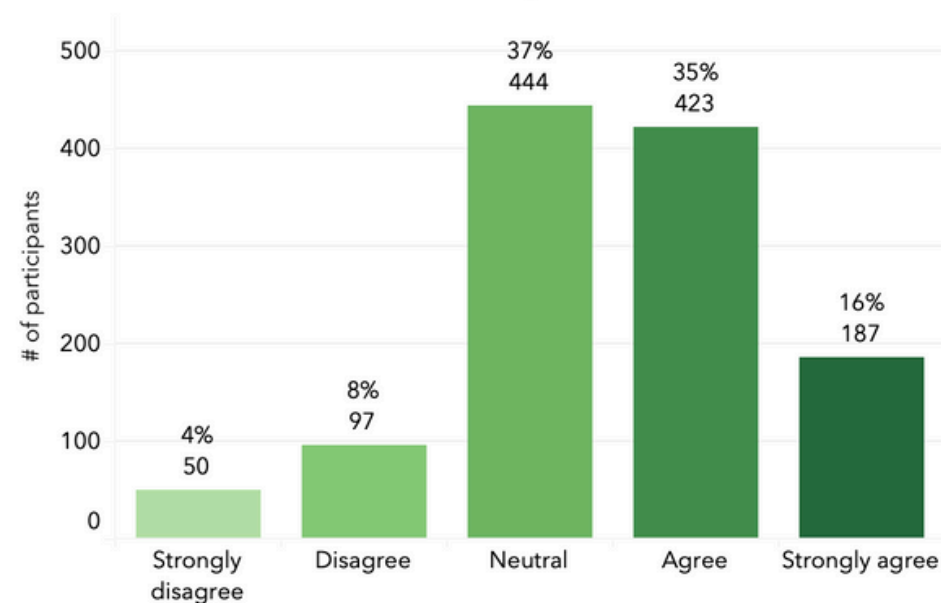
19a

I feel a connection to my place of residence



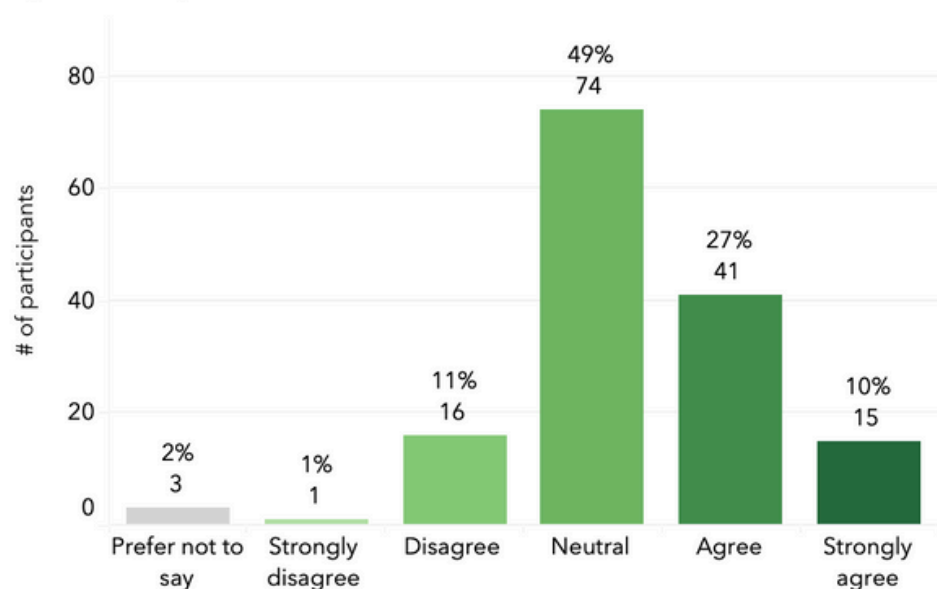
19b

I feel a connection to one of the study areas



19c

My sense of place or connection to where I live has increased



19d

My sense of place or connection to the study area has increased

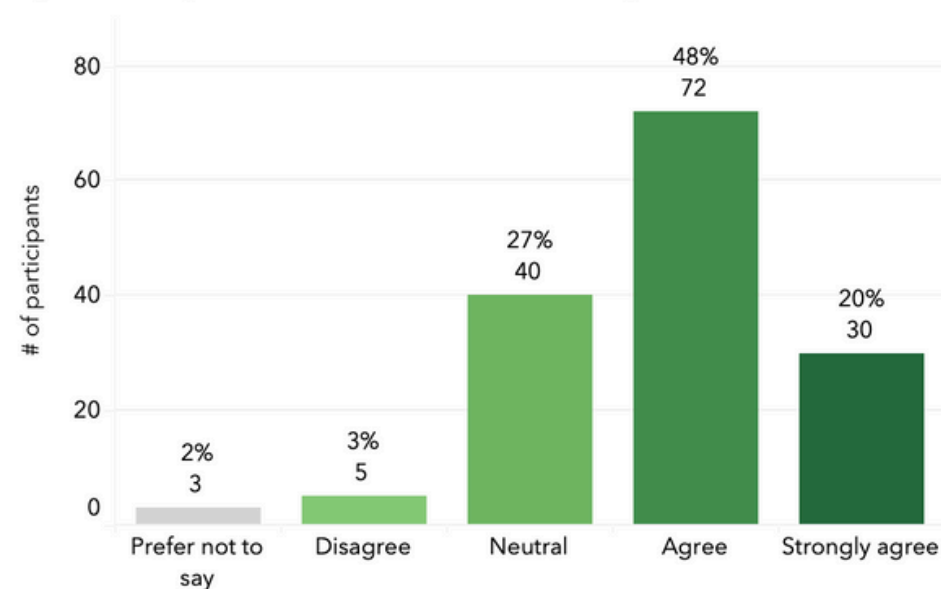
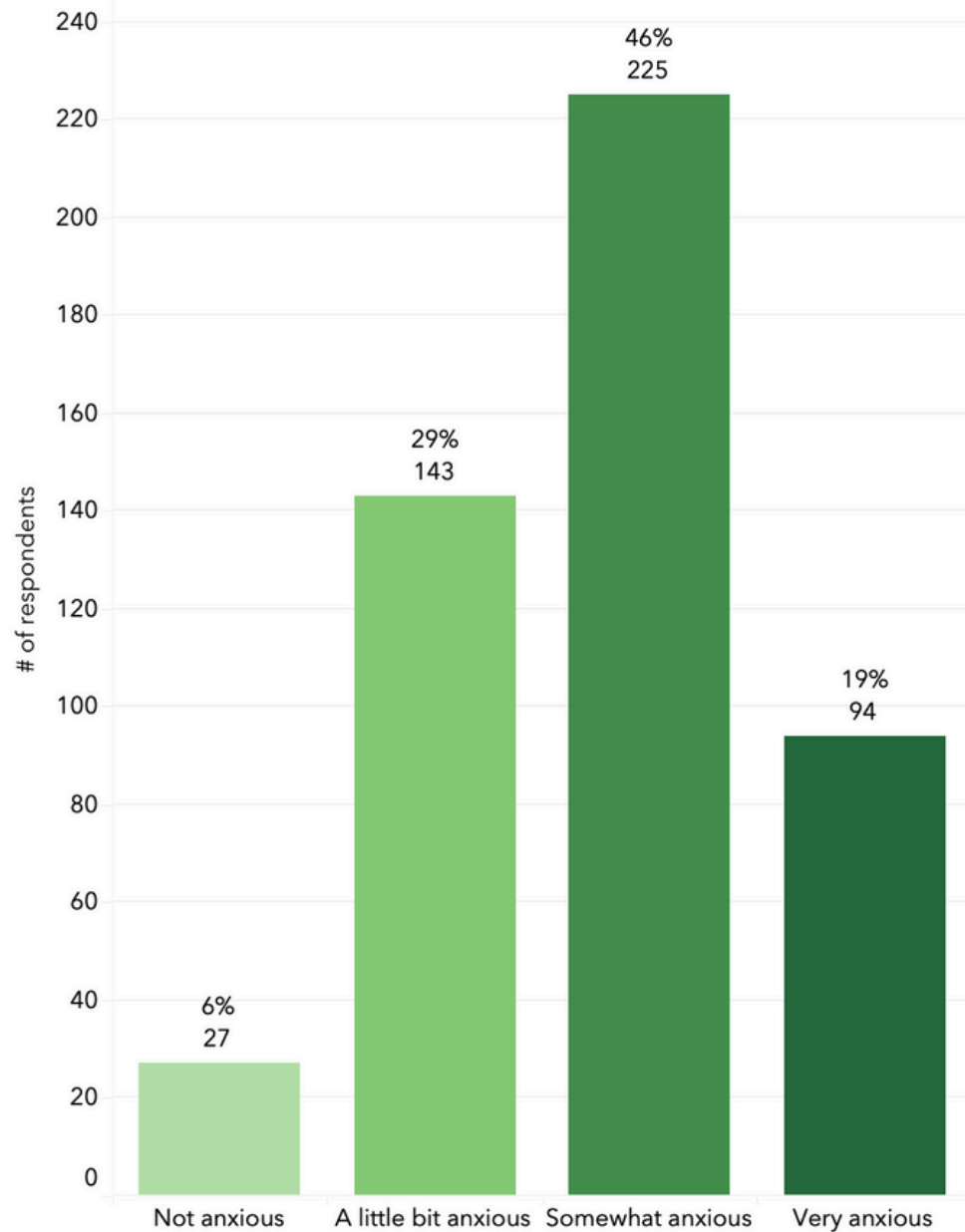


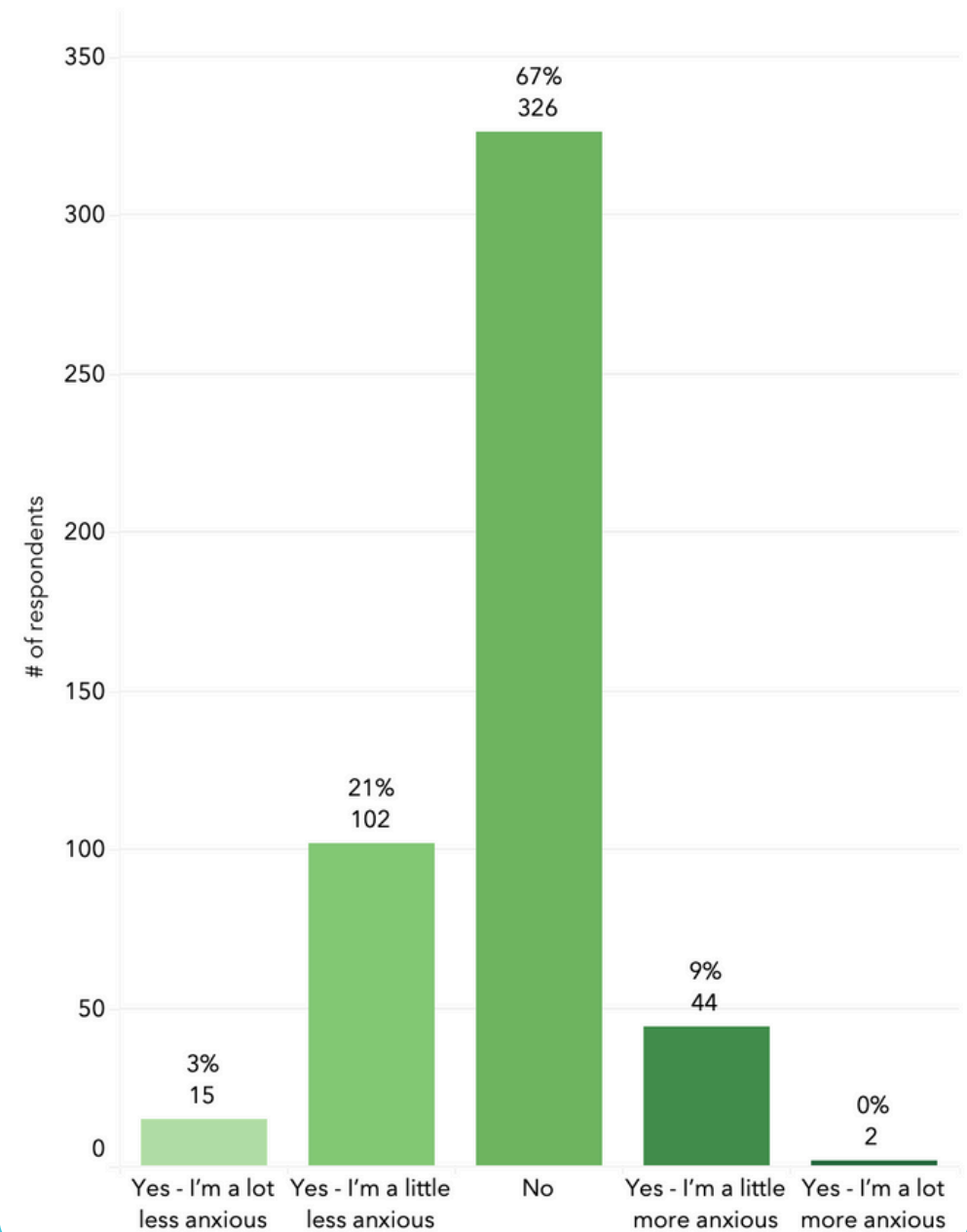
Figure 19 - Participant change in connection to place

What is your current level of climate anxiety?



20a

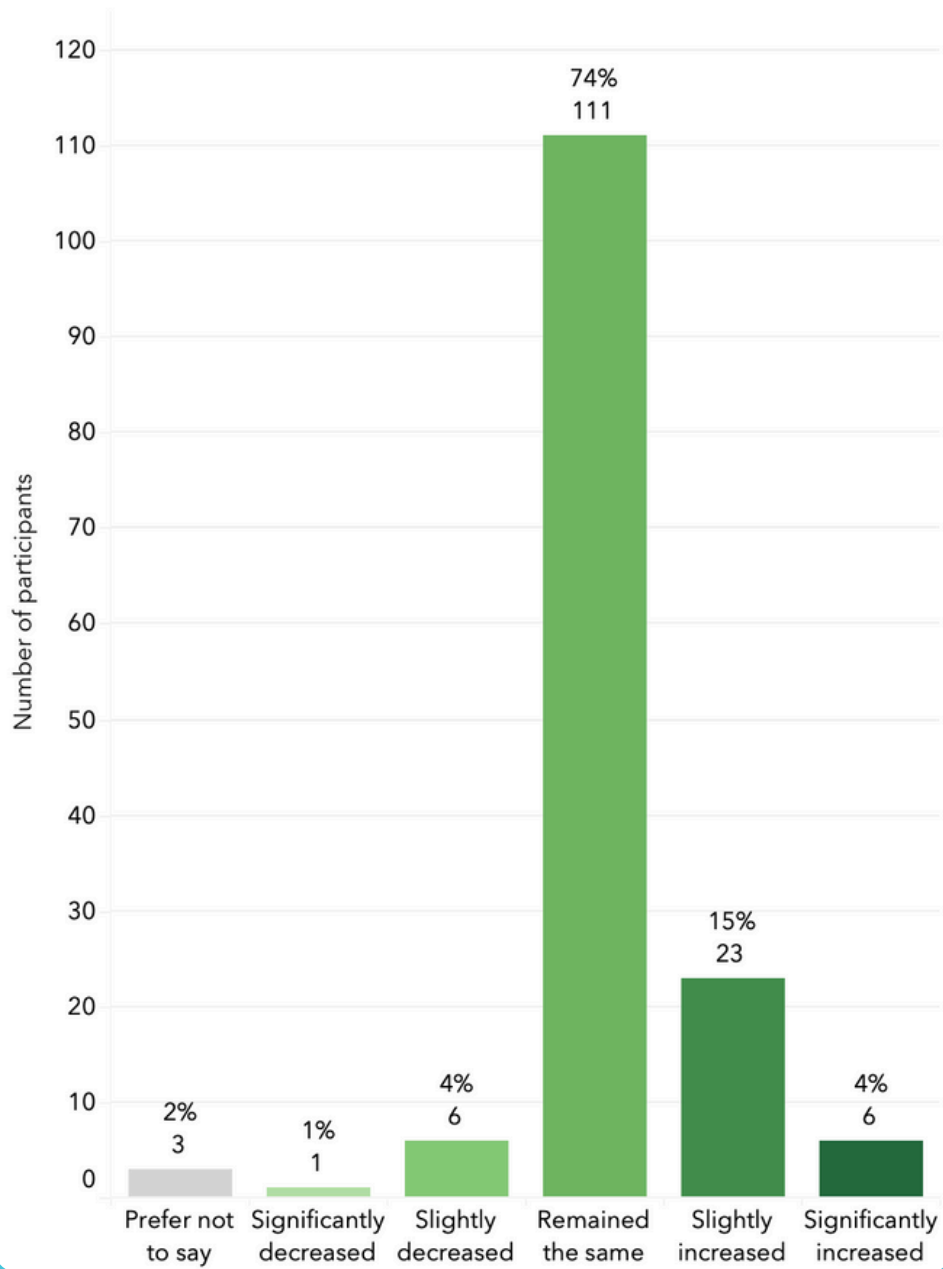
Has involvement in the Deep Time training course impacted your levels of climate anxiety?



20b

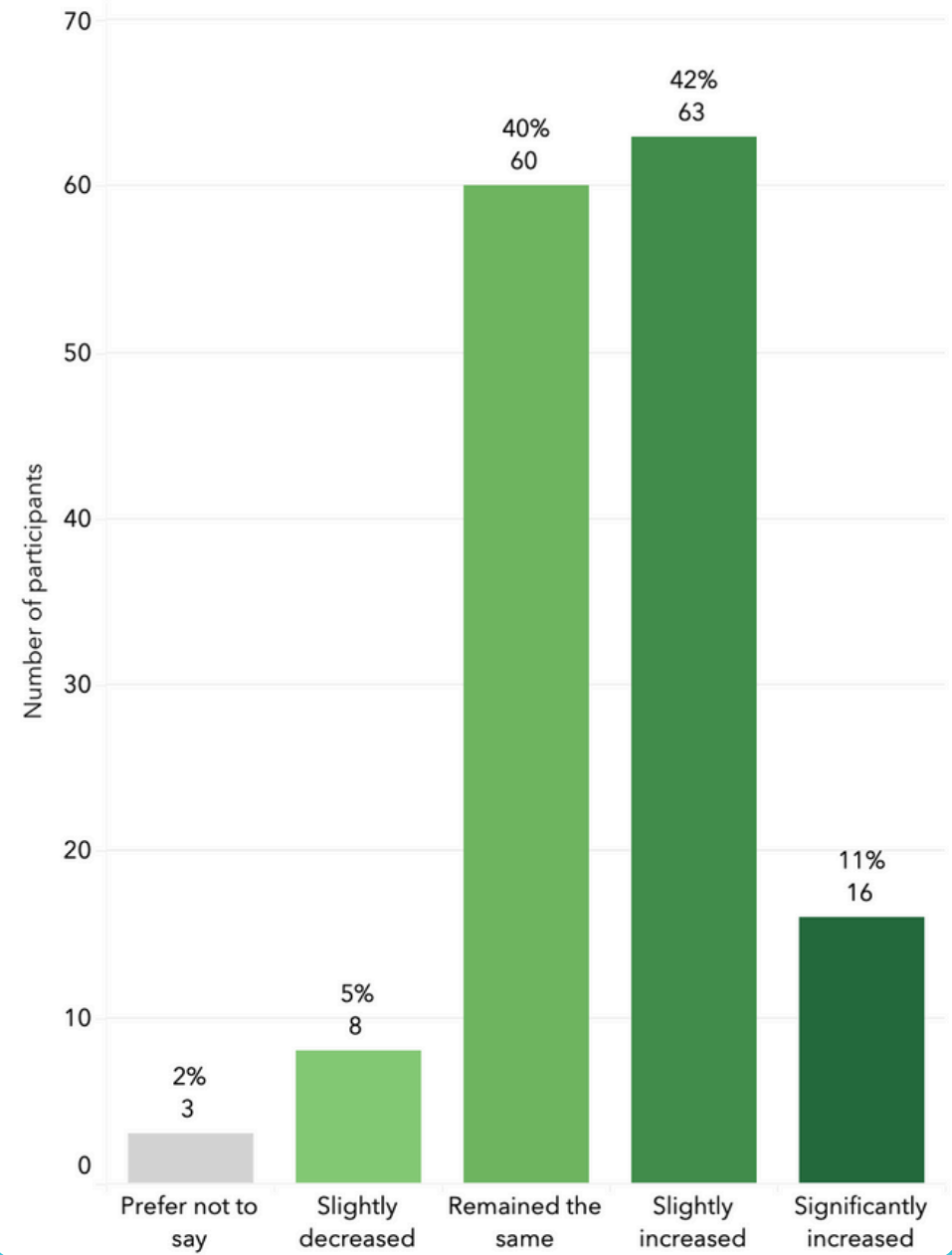
Figure 20 - Change in climate anxiety after training

As a result of my participation, my anxiety about the potential effects of climate change on my life has...



21a

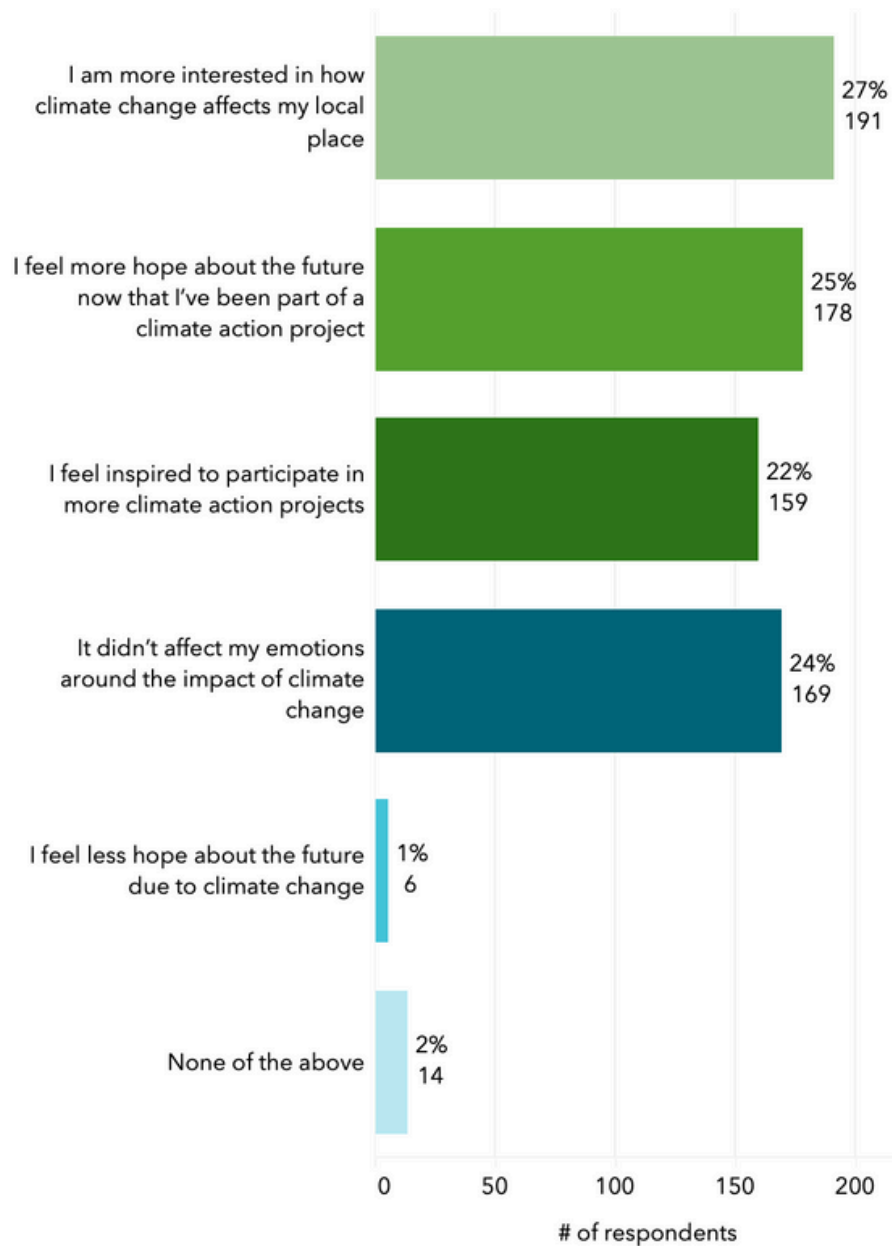
As a result of my participation, my confidence in my ability to make a positive difference in the climate emergency has ...



21b

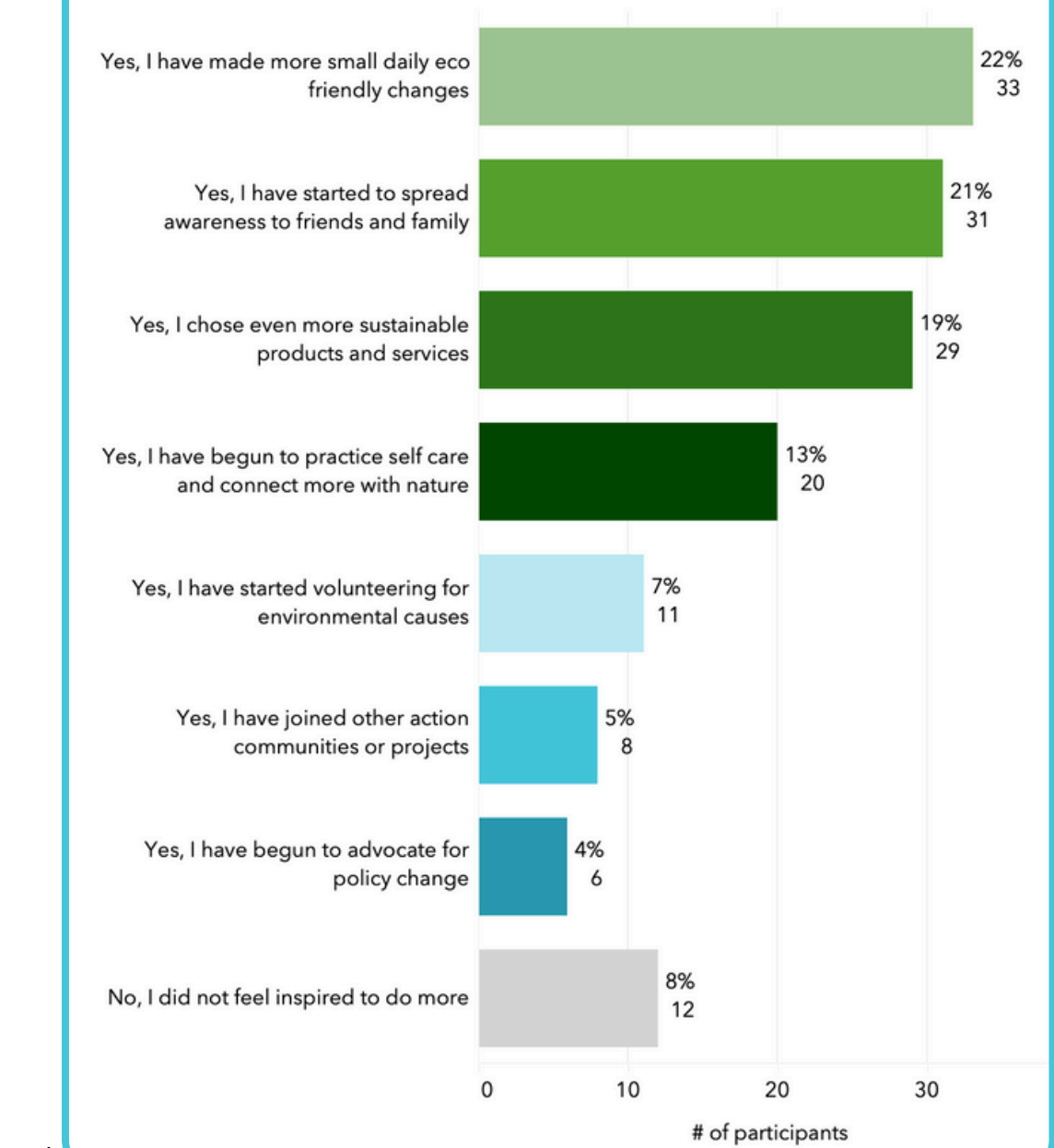
Figure 21 - Change in anxiety and confidence

As a result of my Deep Time training...



22a

Has participation inspired you to make further daily changes ?



22b

Figure 22 - Change in perception and behaviour

Appendix A - Quality assessment methodology and scores for missions 2-5

Quality Assessment methodology for Living England ground survey data

Living England supplied DigVentures with ground survey data points for the area of the Northumberland District, clipped to the total (District) study area boundary as defined by Natural England.

This dataset comprised a total of 2084 ground location points with a primary habitat identification. The data was created between 18th March 2021 and 7th November 2024 with data points categorised by 'Primary LE Habitat'. These habitat categories matched the categories being used by the Deep Time platform for participant habitat mapping, based in turn on the UKBAP categories and the categories used by Living England in the Habitat Probability Map Phase IV and the Living England 2022-2023 habitat mapping (see Appendix D).

The ground survey data was recorded with variable density across the Northumberland District, with some clusters of data points overlapping specific mission areas of Deep Time. The specific distribution of data points within each Deep Time grid is presented within the mission specific tables following (Appendix A).

For the purposes of evaluation, the ground survey data was reviewed using the Deep Time participant grids as a framework, with grid-by-grid assessment. This approach was chosen to give the best indication of the range of variability in accuracy between different participants, with the availability of ground survey data providing an in-built random selection process to the grids being assessed.

The assessment was undertaken in QGIS, with comparative reference made between the accuracy of the Deep Time data, the Living England Phase IV Habitat Probability Map and the Living England LE 2022 – 2023 habitat probability map. The Living England ground survey points were colour-coded by habitat to match the categorisation adopted by Living England for the Habitat Probability Map, along with the Deep Time data.

A score of '1' was given where a mapped Deep Time, Phase IV and LE 2022-2023 habitat polygon matched a Living England ground survey data point, and a score of '0' was given where there was no match.

Where a data point sat on the boundary between two mapped habitat polygons, the GIS map view was zoomed to the maximum extent necessary to define which side of the polygon boundary the point was recorded. The scoring methodology was maintained with an absolute of yes/no for accuracy, regardless of if the correct habitat was identified in the adjacent polygon – the habitat at the exact location of the ground survey point was used to define whether a polygon was correct or not.

Datasets were then compared and scored by tabular spreadsheet recording which map had the most habitats correctly matched to the ground survey points for each mission. The results of this process are presented in the following tables.



Appendix A: M2 - Quality assessment scores for Mission 2

Hadrian's Wall – Mission 2														
	Deep Time grid name	Number of LE ground survey points	Deep Time matched habitats	Phase IV matched habitats	LE 2022/2023 matched points	PIV 100%	LE 100%	DT 100%	DT is best data	All three are equal	DT more matches than one, tied with other	DT in middle	DT fewer matches than one, tied with other	DT has least matches
1	tricky-scheme-272	1	1		1		1	1			1			
2	outgoing-price-802	2	2	1	1			1	1					
3	fearless-committee-101	10	1	9	9									1
4	small-apartment-198	3	3	3	3	1	1	1		1				
5	soupy-response-988	2	2	2	2	1	1	1		1				
6	eager-examination-524	4	3	2	4		1					1		
7	profitable-goal-772	2	2	2		1		1			1			
8	notable-plan-690	7		6	5									1
9	trained-topic-953	2		2	2	1	1							1
10	excellent-relative-133	3		1	3		1							1
11	dimwitted-user-712	21	13	9	14							1		
12	grandiose-user-129	1	1	1	1	1	1	1		1				
13	intelligent-room-526	3	2	2	3		1				1			
14	accurate-sail-638	2	2	1	1			1	1					
15	dense-conference-324	6	3	6	5	1								1
16	blissful-bedroom-904	7	5	3	2				1					
17	shy-collection-306	17	17	16	15			1	1					
18	enchanted-coast-551	3	3	3	3	1	1	1		1				
19	dual-battle-684	2	2	1	2		1	1			1			
20	voluminous-iron-778	6	6	5	4			1	1					
21	outgoing-bit-502	4	4	3	2			1	1					
22	early-city-185	2	2	2		1		1			1			
23	red-driver-380	6	2	2	2					1				
24	austere-lawyer-341	1	1	1	1	1	1	1		1				
25	yellow-ladder-399	10	6	4	9							1		
26	legitimate-project-515	3	2	2	2					1				

27	any-guitar-846	8	2	1	6							1		
28	obedient-process-712	1												1
29	uncommon-orange-946	3	2	3	3	1	1							1
30	rundown-evening-389	1	1	1	1	1	1	1		1				
31	loyal-bother-614	7	6	3	6						1			
32	familiar-responsibility-541	6	5	3	5						1			
33	dramatic-competition-300	1		1	1	1	1							1
34	dry-scale-620	8	7	7	7					1				
35	quintessential-unit-222	6	3	6	3	1							1	
	Total	171	111	114	128	13	14	15	6	9	7	4	1	8

Detailed Habitat (UKBAP & Phase IV)	Colour
Acid, Calcareous, Neutral grassland	
Arable and Horticultural	
Bare Ground	
Bare Sand	
Bog	
Bracken	
Broadleaved, Mixed and Yew Woodland	
Built-up Areas and Gardens	
Coastal Saltmarsh	
Coastal Sand Dunes	
Coniferous Woodland	
Dwarf Shrub Heath	
Fen, Marsh and Swamp	
Improved Grassland	
Scrub	
Water	
Alt Water	

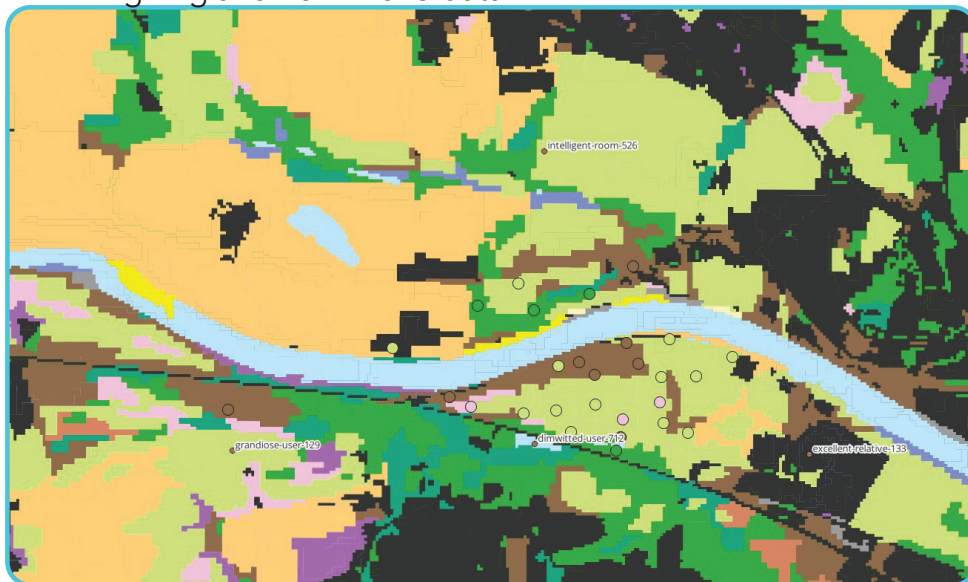
Deep Time data



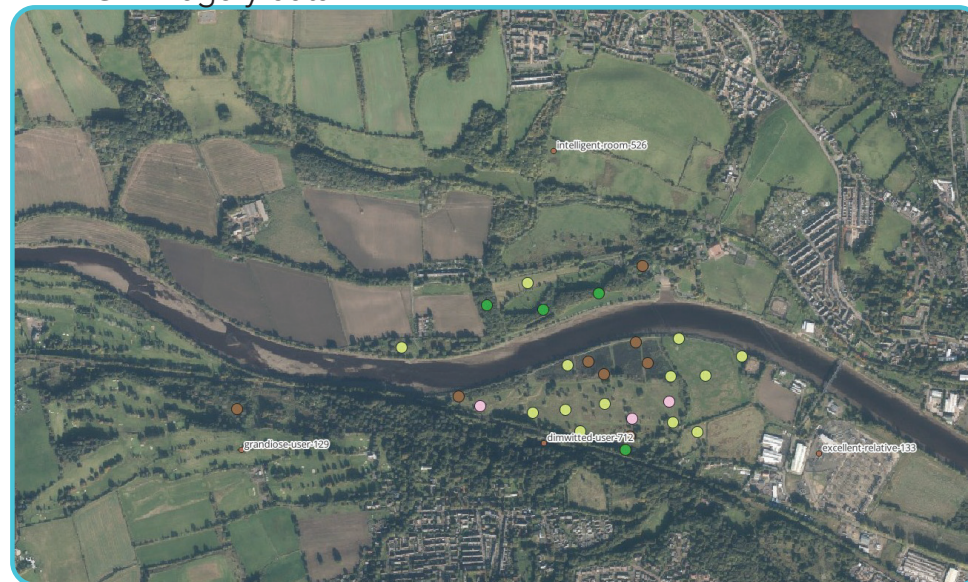
Phase IV data



Living England 2022-2023 data



APGB imagery data



Grids:
grandiose-user-129
excellent-relative-133
dimwitted-user-712*
intelligent-room-526

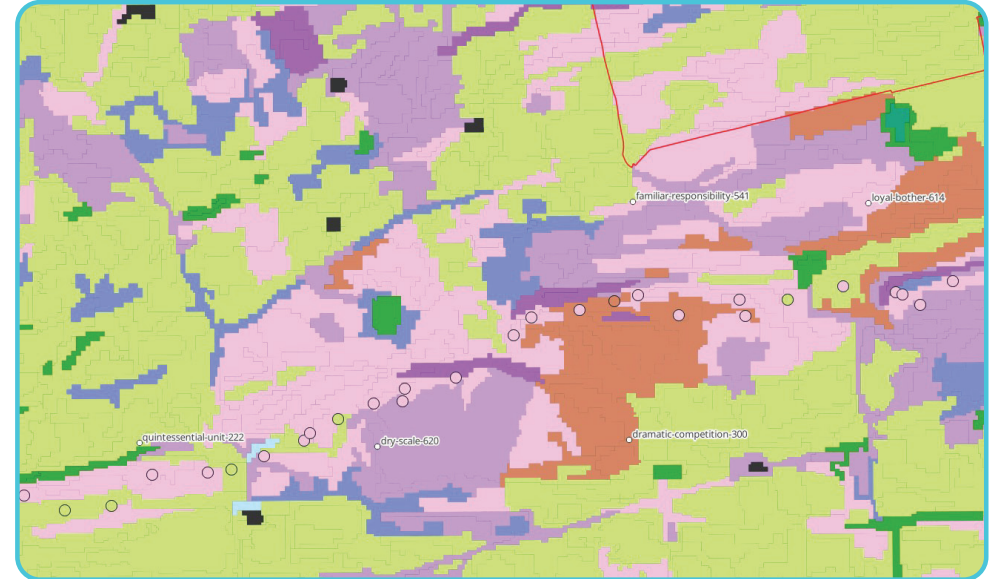
28 LE points total,
16 LE data points
match DT data, LE23
has 21, PIV matches 13.

* bold grid-title represents named grid the screenshots were labelled and saved by, for project reference only.
NB. Mission 2, Hadrian's Wall corridor was the only mission to use the Phase IV habitat probability map as reference data; M2 participants didn't have LE 2022-2023 data.

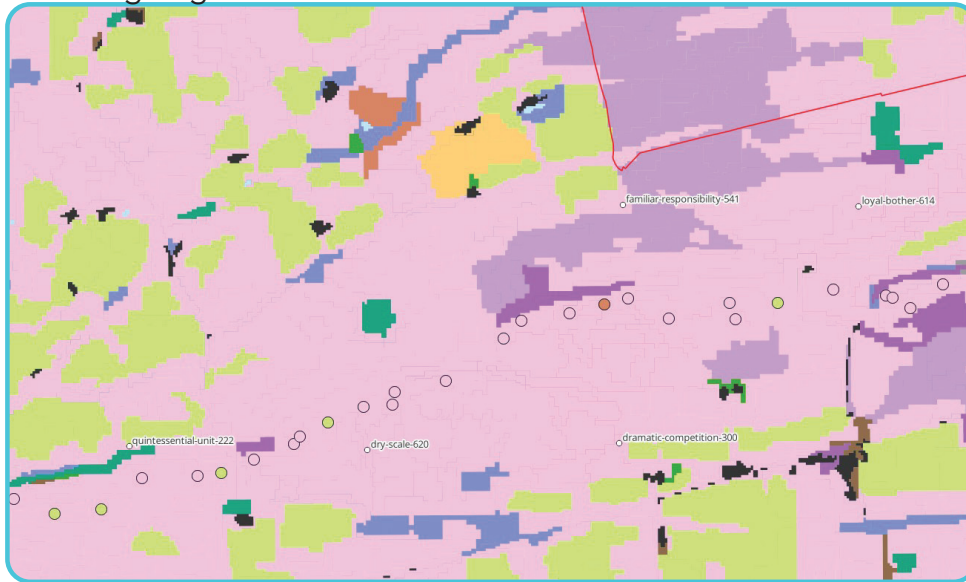
Deep Time data



Phase IV data



Living England 2022-2023 data



APGB imagery data



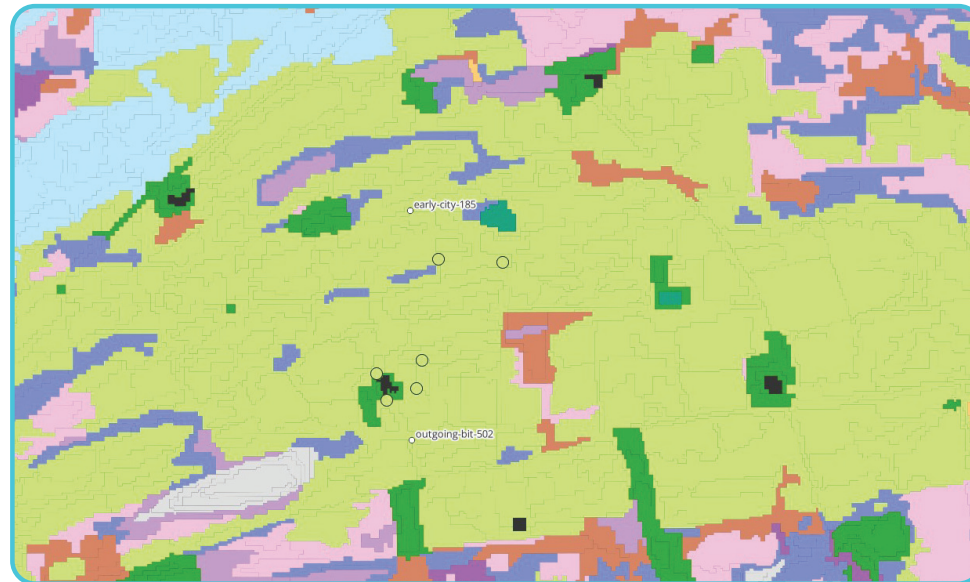
Grids:
 quintessential-unit-222
 dry-scale-620
 familiar-responsibility-541
dramatic-competition-300
 loyal-bother-614

28 LE points total,
 21 LE data points
 match DT data, LE23
 has 22, PIV matches 20.

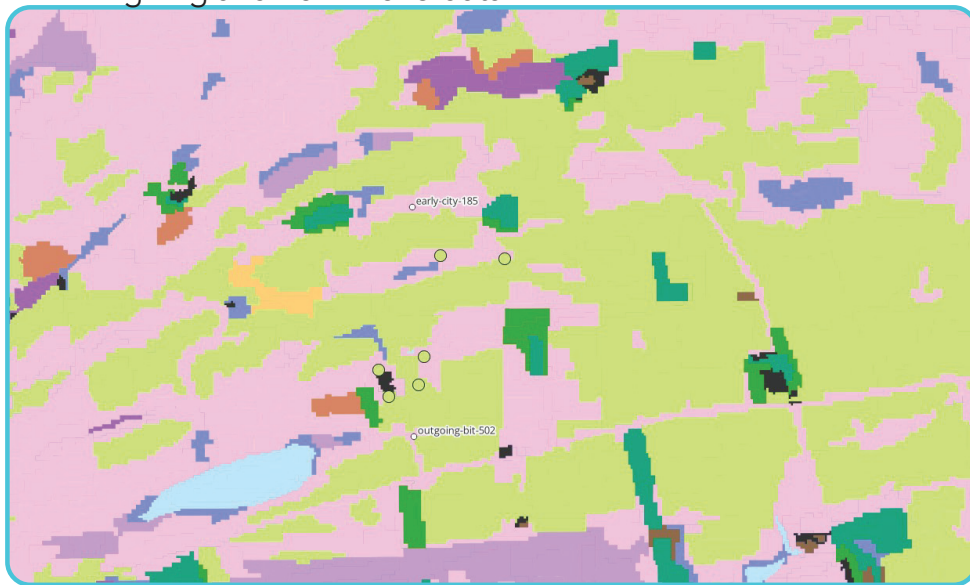
Deep Time data



Phase IV data



Living England 2022-2023 data



APGB imagery data



Grids:
early-city-185
outgoing-bit-502

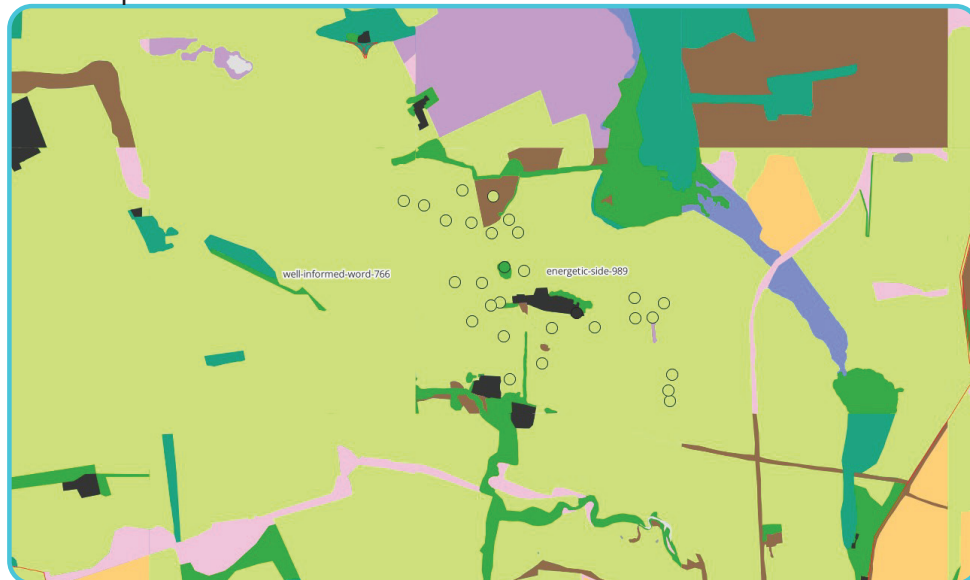
6 LE points total,
6 LE data points
match DT data, LE23
has 2, PIV matches 5.

App A: M2-3 - Hadrian's Wall corridor: detailed results 3.

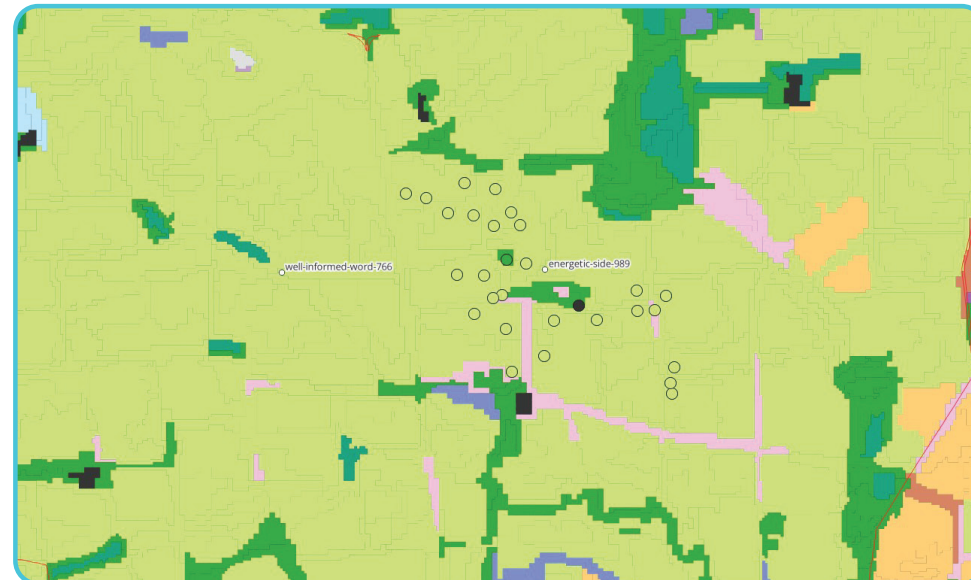
Appendix A: M3 - Quality assessment scores for Mission 3

Wallington Estate – Mission 3														
	Deep Time grid name	Number of LE ground survey points	Deep Time matched habitats	Phase IV matched habitats	LE 2022/2023 matched points	PIV 100%	LE 100%	DT 100%	DT is best data	All three are equal	DT more matches than one, tied with other	DT in middle	DT fewer matches than one, tied with other	DT has least matches
1	honest-feedback-740	6	6	6	6	1	1	1		1				
2	trusting-summer-818	8	5	5	4						1			
3	precious-screen-775	3	1	2	1								1	
4	lean-savings-478	1	1	1		1		1			1			
5	itchy-effort-889	26	14	15	14								1	
6	youthful-wall-793	2	2	2	1	1		1			1			
7	pastel-fan-190	5	1	1							1			
8	energetic-side-989	28	26	25	24				1					
9	well-informed-word-766	1	1	1	1	1	1	1		1				
	Total	80	57	58	51	4	2	4	1	2	4	0	2	0

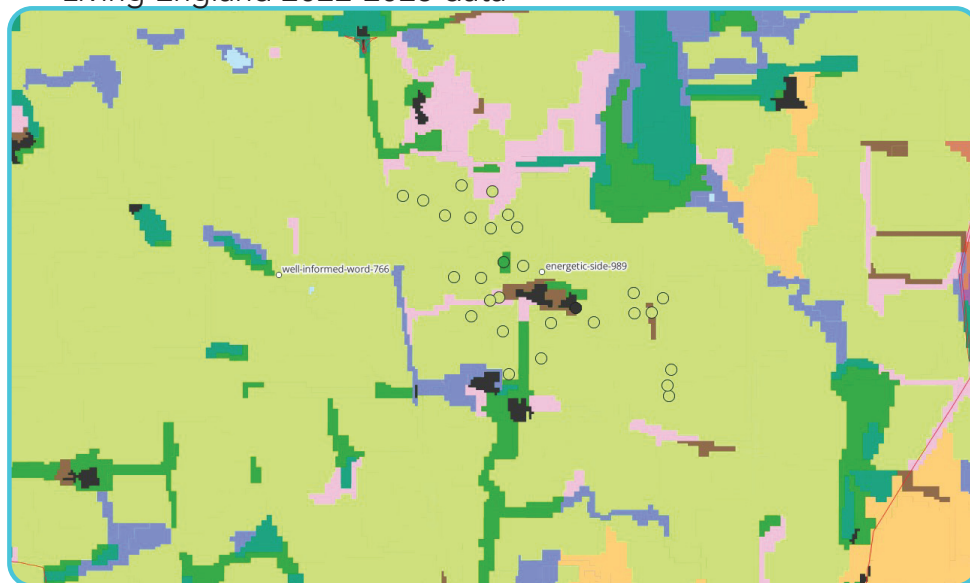
Deep Time data



Phase IV data



Living England 2022-2023 data



APGB imagery data



Grids:
well-informed-word-766
energetic-side-989*

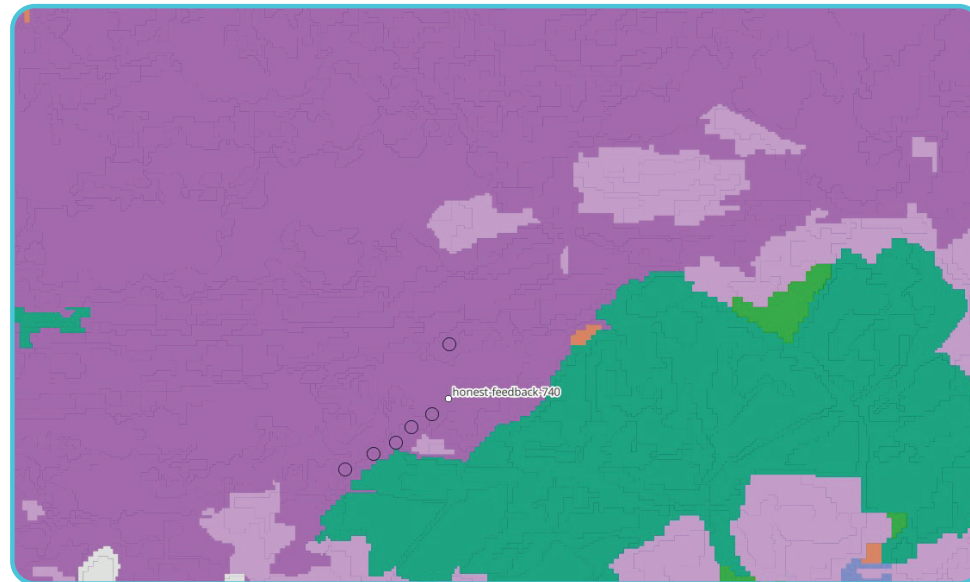
29 LE data points total,
27 match DT data, LE23
has 25, PIV matches 26.

App A: M3-1 - Wallington Estate: detailed results 1.

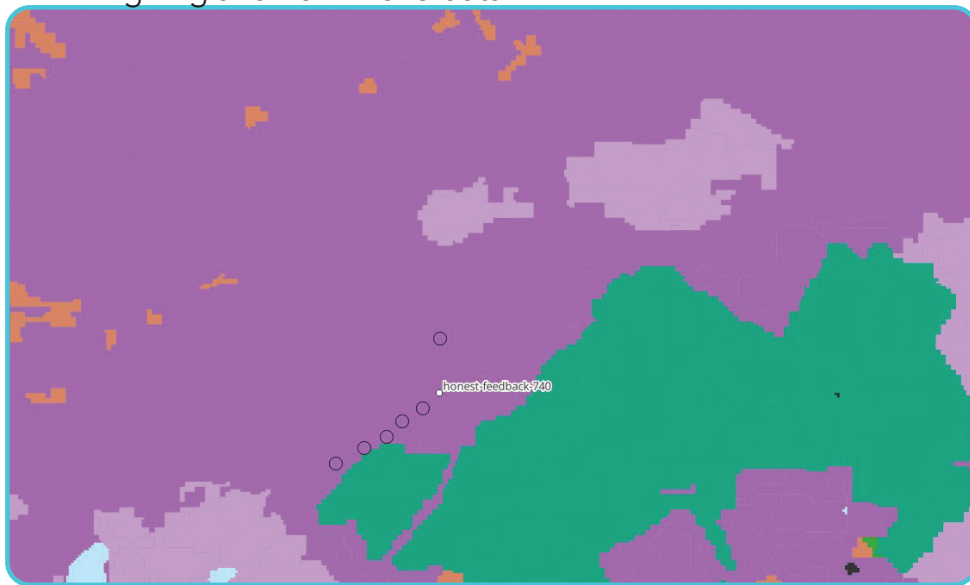
Deep Time data



Phase IV data



Living England 2022-2023 data



APGB imagery data

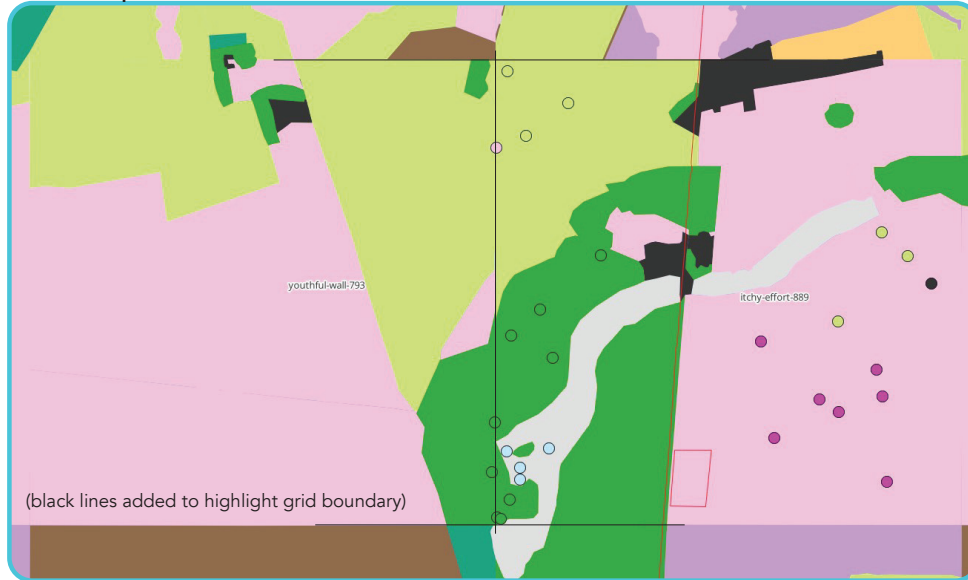


Grids:
energetic-side-989

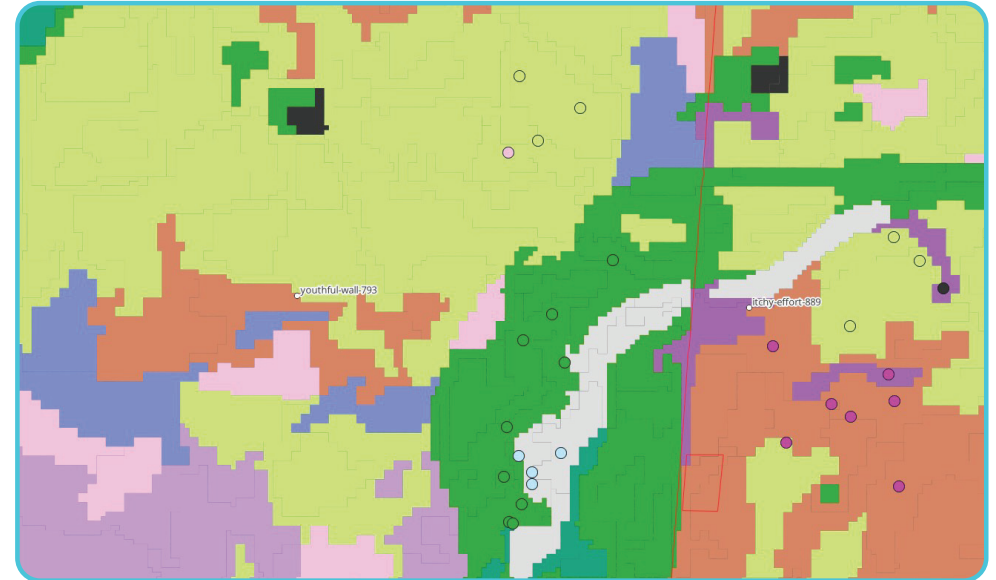
6 LE data points, all
match DT data, LE23
and PIV perfectly.

App A: M3-2 - Wallington Estate: detailed results 2.

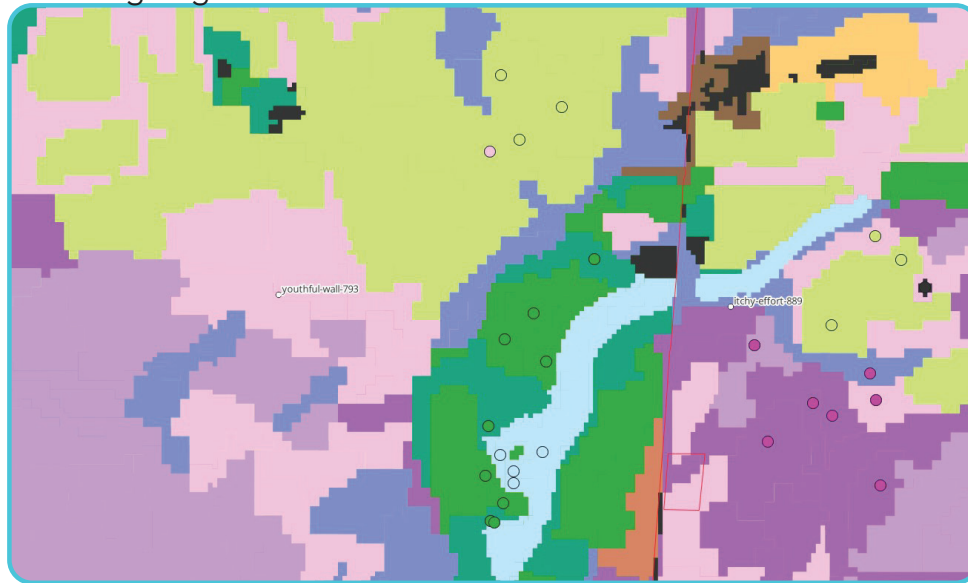
Deep Time data



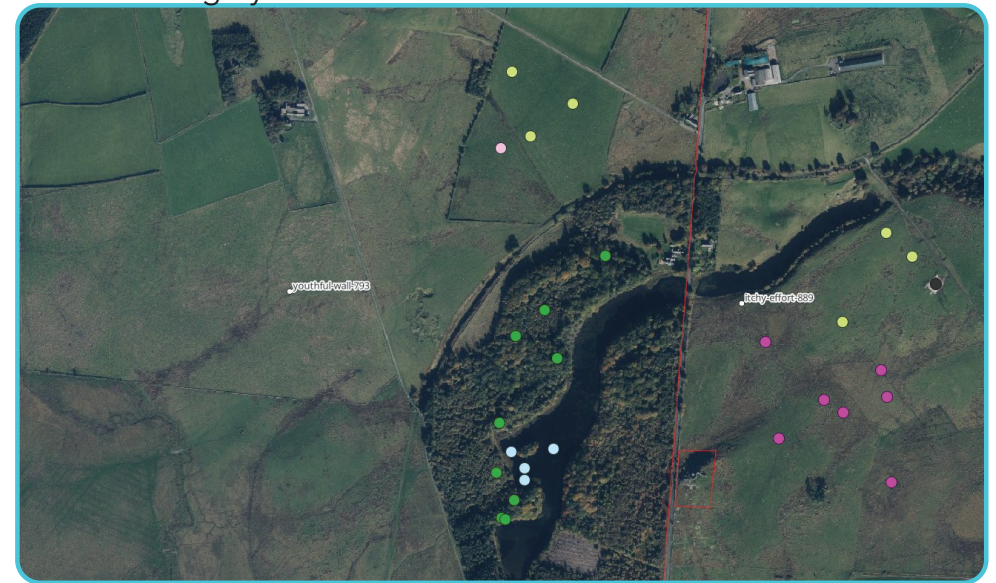
Phase IV data



Living England 2022-2023 data



APGB imagery data



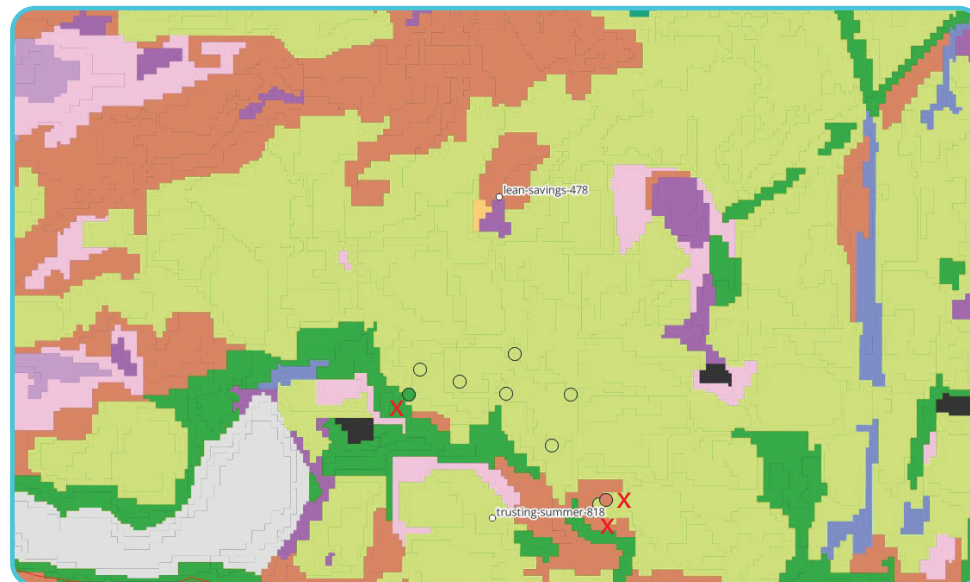
Grids:
itchy-effort-889 (x26)
youthful-wall-793 (x2)

28 LE data points total,
16 match DT data, LE23
has 16, PIV matches 17.
All struggle with Fen, Marsh, Bog.
LE22-23 does less well with woods.

Deep Time data



Phase IV data



Living England 2022-2023 data

'X' indicates incorrect IDs



APGB imagery data



Grids:
lean-savings-478
trusting-summer-818

9 LE data points total,
6 match DT data, LE23
has 4, PIV matches 6 too.
Absolute locations of LE points
are always used.

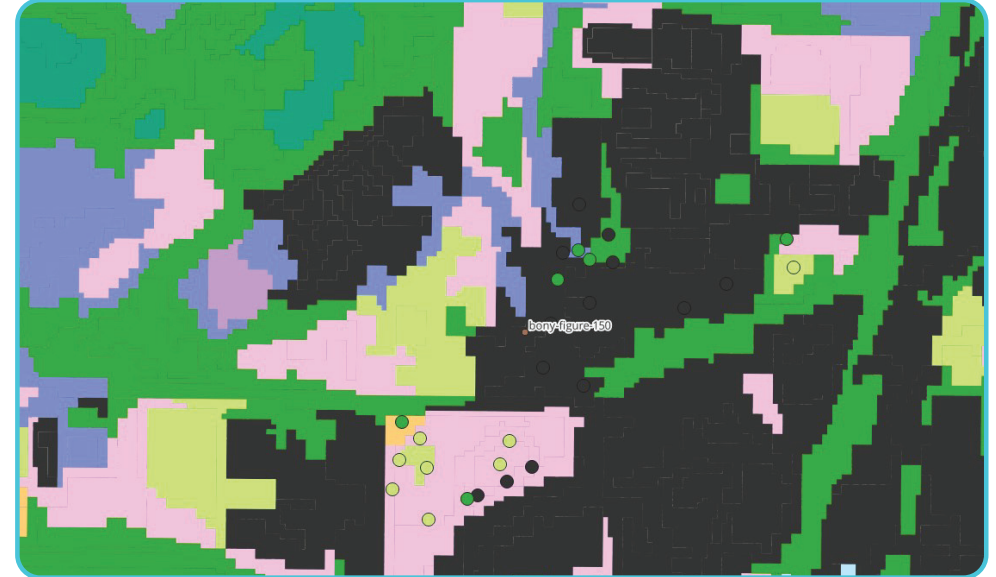
Appendix A: M4 - Quality assessment scores for Mission 4

Brightwater Landscape – Mission 4														
	GRIDNAME	Number of LE ground survey points	Deep Time matched habtats	Phase IV matched habitats	LE 2022/2023 matched points	PIV 100%	LE 100%	DT 100%	DT is best data	All three are equal	DT more matches than one, tied with other	DT in middle	DT fewer matches than one, tied with other	DT has least matches
1	sunny-time-722	3	3	2	2			1	1					
2	bony-figure-150	25	19	12	20				1					
	Total	28	22	14	22	0	0	1	2	0	0	0	0	0

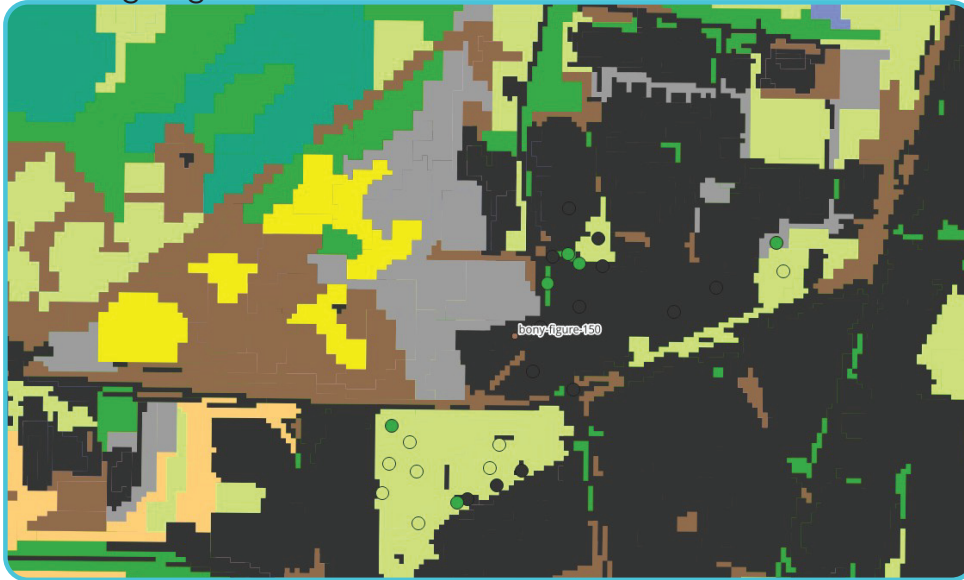
Deep Time data



Phase IV data



Living England 2022-2023 data



APGB imagery data

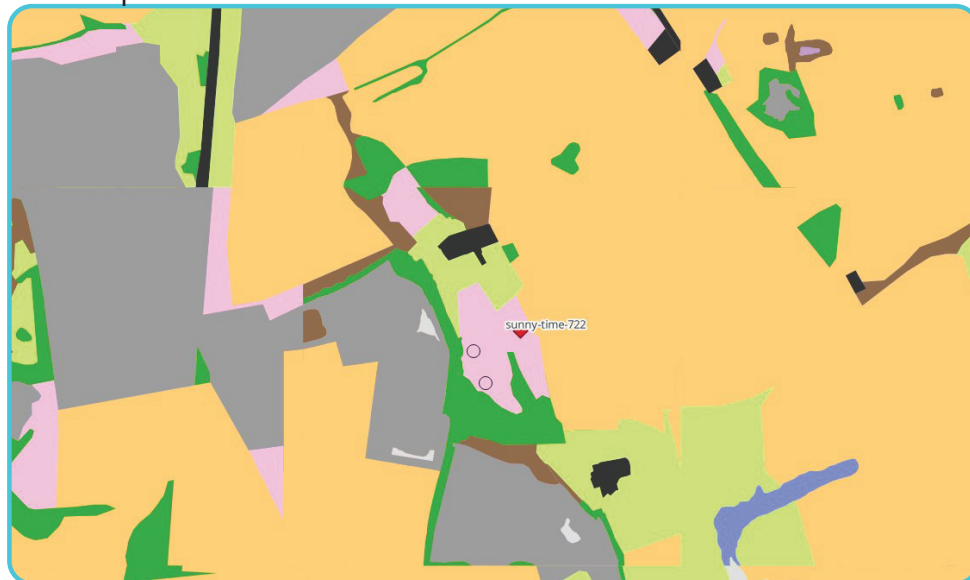


Grids:
bony-figure-150

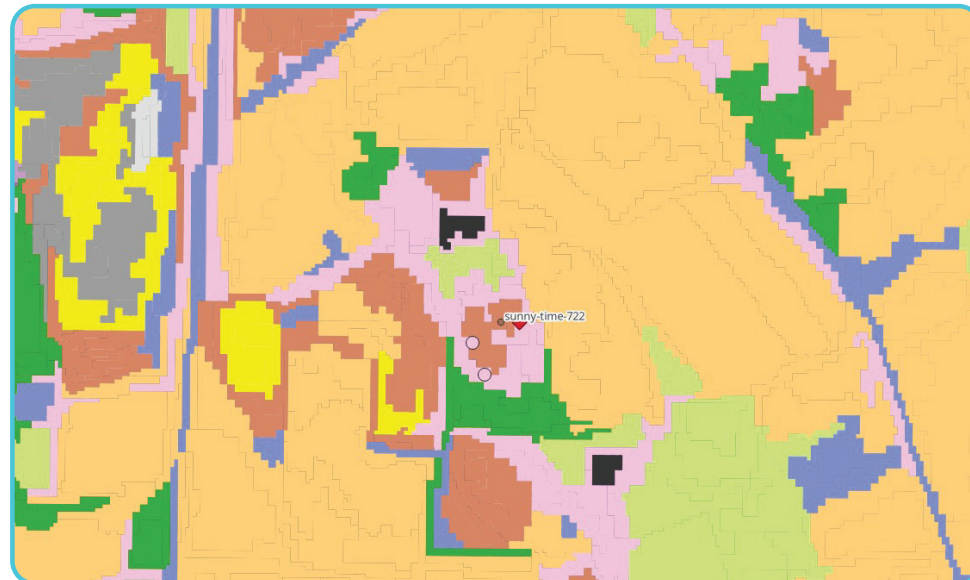
25 LE data points total,
19 match DT data, LE23
has 20, PIV matches 12.
Arguably DeepTime data is
more accurate than score, due
to interpretation of 'urban' etc.

NB. Missions 3-5 used Living England LE 2022-2023 data as reference; Phase IV habitat probability map was not included as a reference layer.

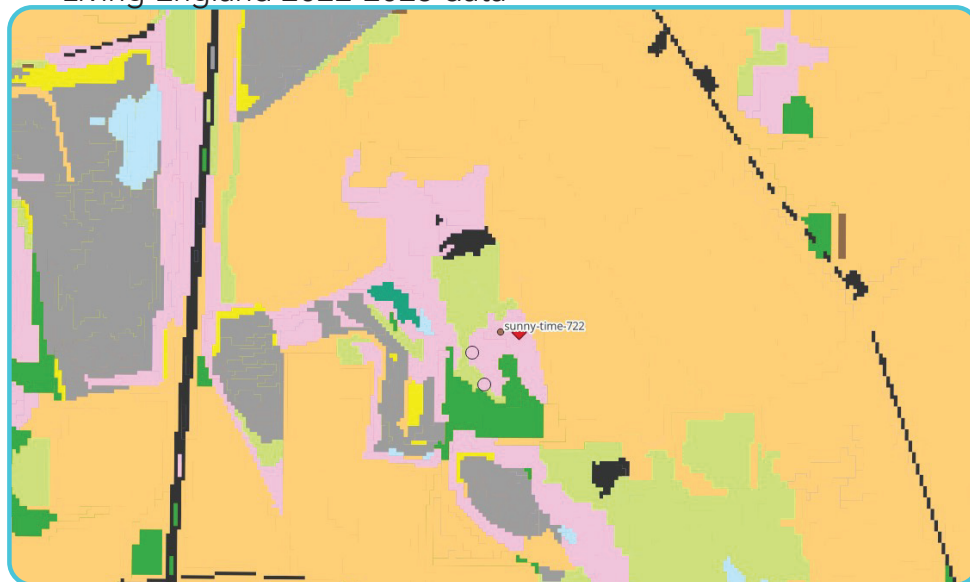
Deep Time data



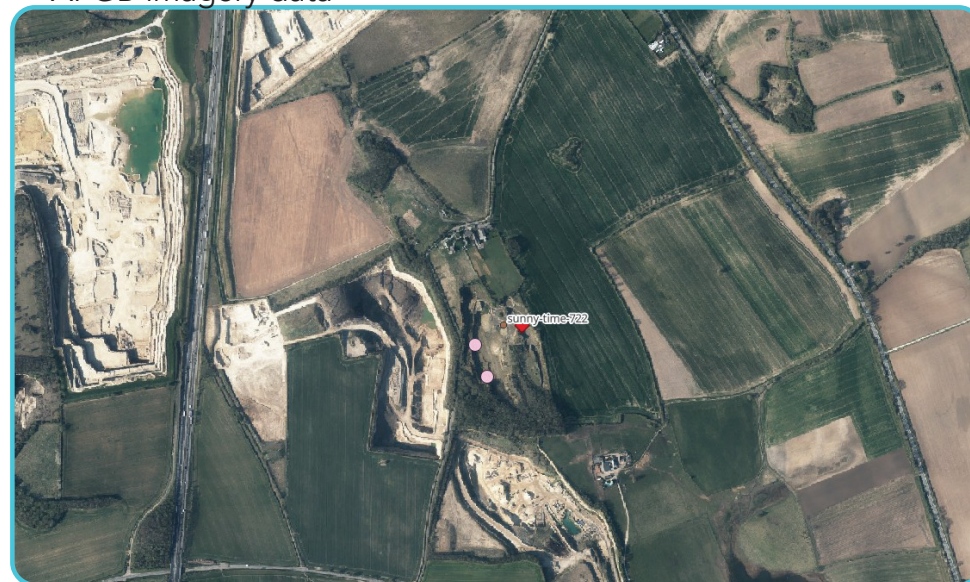
Phase IV data



Living England 2022-2023 data



APGB imagery data



Grids:
sunny-time-722

3 LE data points total,
3 match DT data, LE23
has 2, PIV matches 2.
Red rhombus = 'multiple habitats'
but Acid Calcareous Grassland was the first

App A: M4-2 - Brightwater Landscape: detailed results 2.

There were only two grids within Brightwater study area with LE ground survey data points.

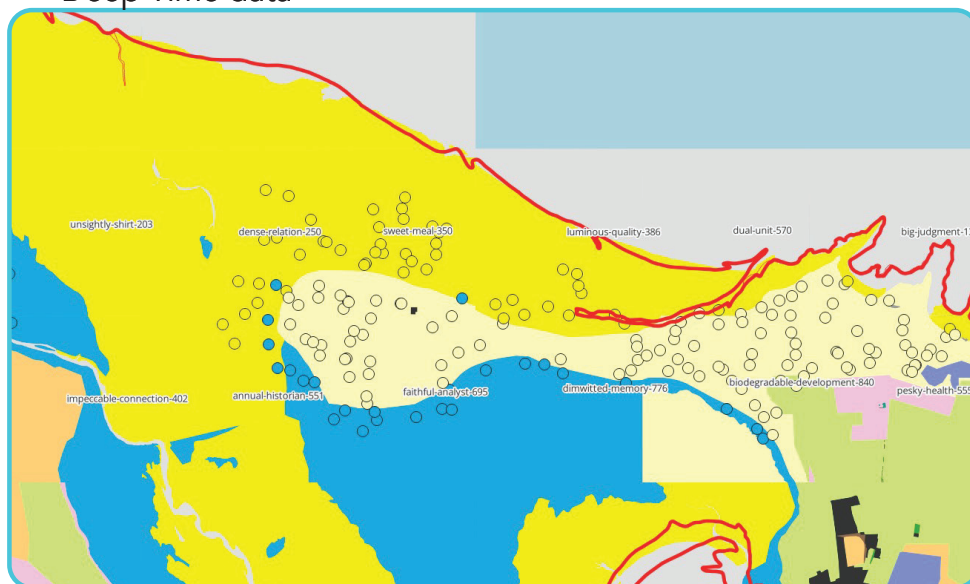
Appendix A: M5 - Quality assessment scores for Mission 5

Northumberland Coast National Landscape – Mission 5														
	Deep Time grid name	Number of LE ground survey points	Deep Time matched habitats	Phase IV matched habitats	LE 2022/2023 matched habitats	Phase IV 100%matched	2022/2023 100% matched	DT 100%	DT is best data	All three are equal	DT more matches than one, tied with other	DT in middle	DT fewer matches than one, tied with other	DT has least matches
1	faithful-version-662	2	2	1	2		1	1			1			
2	dramatic-mixture-666	3	2	3	3	1	1							1
3	parched-fruit-131	1	1	1	1	1	1	1		1				
4	naive-zone-183	13	12	10	11				1					
5	unsightly-shirt-203	2	2	2	1	1		1			1			
6	impeccable-connection-402	1	1	1	1	1	1	1		1				
7	dense-relation-250	16	14	13	3				1					
8	sweet-meal-350	34	33	27	11				1					
9	luminous-quality-386	11	11	9				1	1					
10	dual-unit-570	12	11	10	10				1					
11	big-judgment-131	8	8	8	8	1	1	1		1				
12	annual-historian-551	9	6	4	4				1					
13	faithful-analyst-695	29	29	27	28			1	1					
14	dimwitted-memory-776	18	18	17	13			1	1					
15	biodegradable-development-840	37	34	33	35							1		
16	pesky-health-555	24	24	24	24	1	1	1		1				
17	fearless-room-122	1	1	1	1	1	1	1		1				
18	vital-back-369	1	1	1	1	1	1	1		1				
19	thorough-driver-366	2	2	1				1	1					
20	courageous-layer-149	1	1	1		1		1			1			
21	finished-assignment-199	2	2	1				1	1					
22	vigorous-chart-839	3	3	3	2	1		1			1			
23	oval-atmosphere-688	1		1		1							1	
24	weary-understanding-356	5	2	2	1						1			
25	awkward-government-263	3	2		2						1			

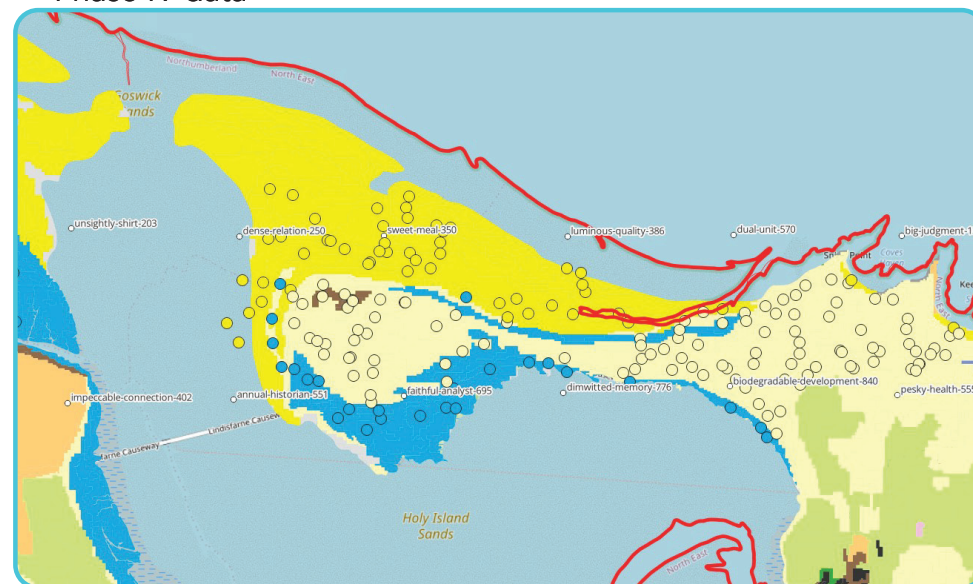
26	this-half-737	5	4	5	3	1						1		
27	cluttered-patient-262	5	3	3	1						1			
28	pretty-profit-881	3	3	3	3	1	1	1		1				
29	junior-passage-652	1	1	1	1	1	1	1		1				
30	scratchy-tip-894	3	2	2	3		1						1	
31	authorized-oil-270	2	2	2	2	1	1	1		1				
32	failing-wall-352	3	3	3	3	1	1	1		1				
33	wide-indication-972	2		1	1									1
34	ruddy-contest-739	4	2	3	2								1	
35	sharp-lawyer-937	9	5	7	8									1
36	wiry-age-195	7	7	7	7	1	1	1		1				
37	tender-permission-526	9	8	8	8					1				
38	flickering-measurement-978	4	4	4	4	1	1	1		1				
39	acceptable-revenue-295	6	5	5	5					1				
40	orange-body-374	6	6	5	6		1	1			1			
41	next-map-326	2	2		2		1	1			1			
42	coarse-pair-402	2	2	2	2	1	1	1		1				
43	famous-wind-449	1			1		1						1	
44	active-buddy-890	1		1	1	1	1							1
45	plaintive-kind-514	4	4	1	4		1	1			1			
46	unwelcome-election-434	3	3	2	3		1	1			1			
47	reliable-pound-155	3	3	3	3	1	1	1		1				
48	delayed-desk-456	3	3	3	2	1		1			1			
49	dense-buddy-983	5	5	5	5	1	1	1		1				
50	other-system-620	2	2	2	2	1	1	1		1				
51	complex-winner-433	1	1	1	1	1	1	1		1				
52	unrealistic-taste-619	3	3	3	3	1	1	1		1				
53	half-self-865	2	2	2	2	1	1	1		1				
54	rubbery-afternoon-791	3	2	3	1	1						1		
55	squeaky-atmosphere-680	5	5	5	4	1		1			1			

56	popular-candidate-770	5	4	4	3						1			
57	athletic-replacement-241	6	3	5	4									1
58	motherly-snow-771	2	2	2	2	1	1	1		1				
59	distorted-cup-990	5	5	5	5	1	1	1		1				
60	spotless-efficiency-544	3	2	2	2					1				
61	mild-meal-909	4	4	3	4		1	1			1			
62	powerful-commission-229	5	5	3	5		1	1			1			
63	nonstop-history-226	6	2	5	4									1
64	urban-chain-383	9	9	7	8			1	1					
65	active-effect-525	9	5	5	5					1				
66	enchanted-gas-766	8	7	7	6						1			
67	which-black-766	3	3	3	3	1	1	1		1				
68	worldly-substance-610	4	4	4	4	1	1	1		1				
69	determined-tennis-605	2	2	2	2	1	1	1		1				
70	impressive-art-608	5	3	3	3					1				
71	handy-height-446	7	6	6	6					1				
	Total	431	380	359	321	34	35	42	11	30	17	3	4	6

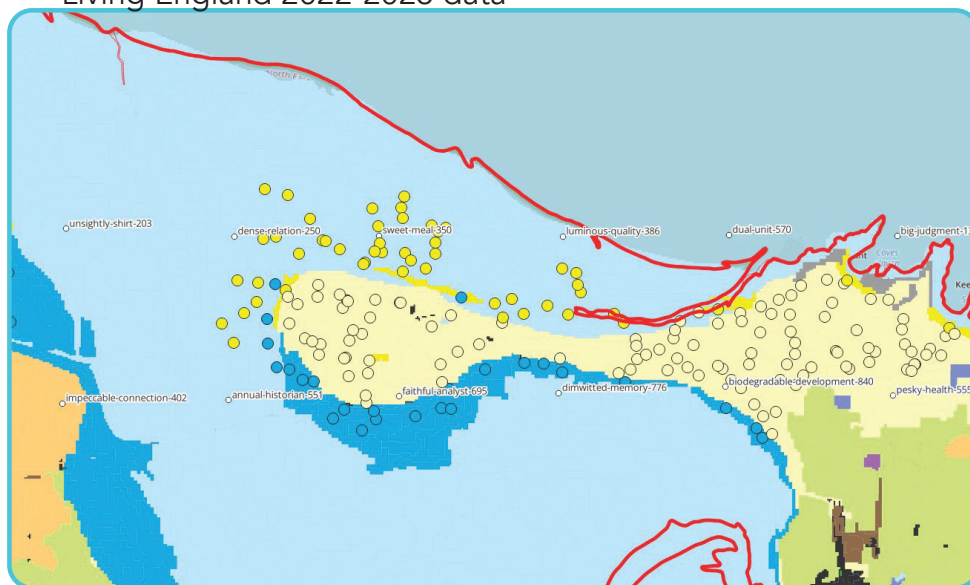
Deep Time data



Phase IV data



Living England 2022-2023 data



APGB imagery data



Grids: unsightly-shirt-203, impeccable-connection-402, **dense-relation-250**, sweet-meal-350, luminous-quality-386, dual-unit-570, big-judgment-131, annual-historian-551, faithful-analyst-695, dimwitted-memory-776, biodegradable-development-840, pesky-health-555

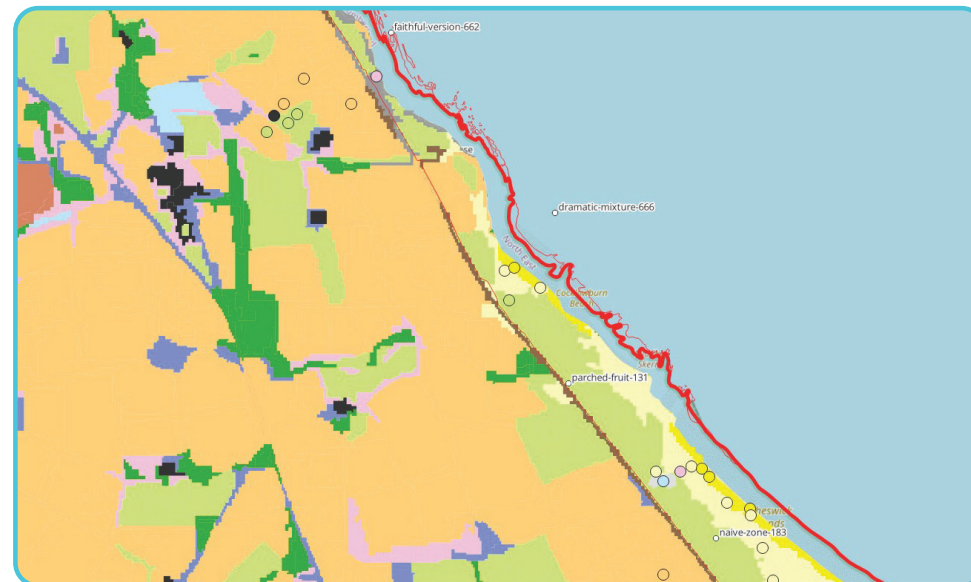
201 LE data points in total,
191 match DT data, LE23
has 138, PIV matches 175.
LE23 uses high-tide line.
Some LE ground data salt marsh areas
unseen by all three polygon layers

App A: M5-1 - Northumberland Coast NL: detailed results 1.

Deep Time data



Phase IV data



Living England 2022-2023 data



APGB imagery data



Grids:
faithful-version-662
 dramatic-mixture-666
 parched-fruit-131
 naive-zone-183

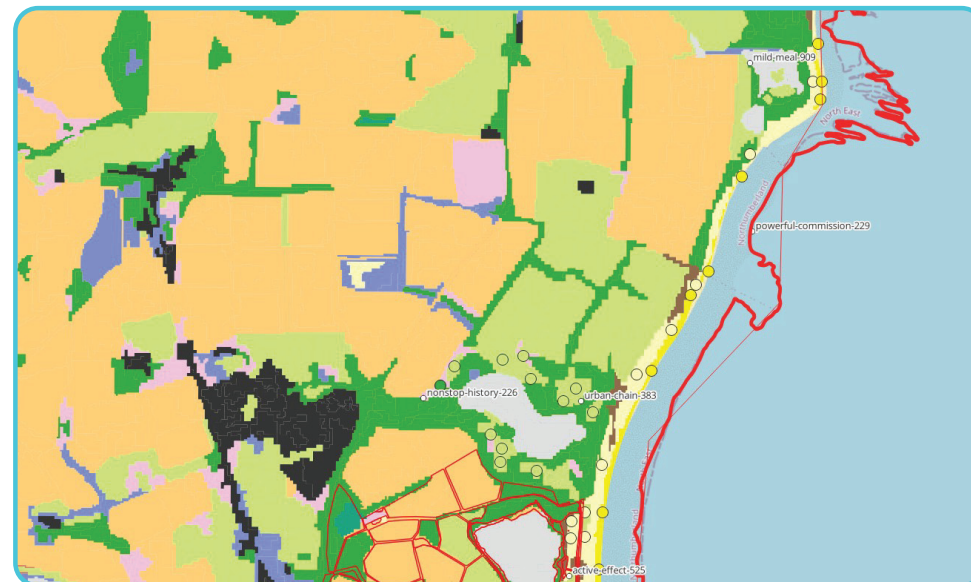
19 LE data points total.
 17 match DT data, LE23
 has 17, PIV matches 15.

App A: M5-2 - Northumberland Coast NL: detailed results 2.

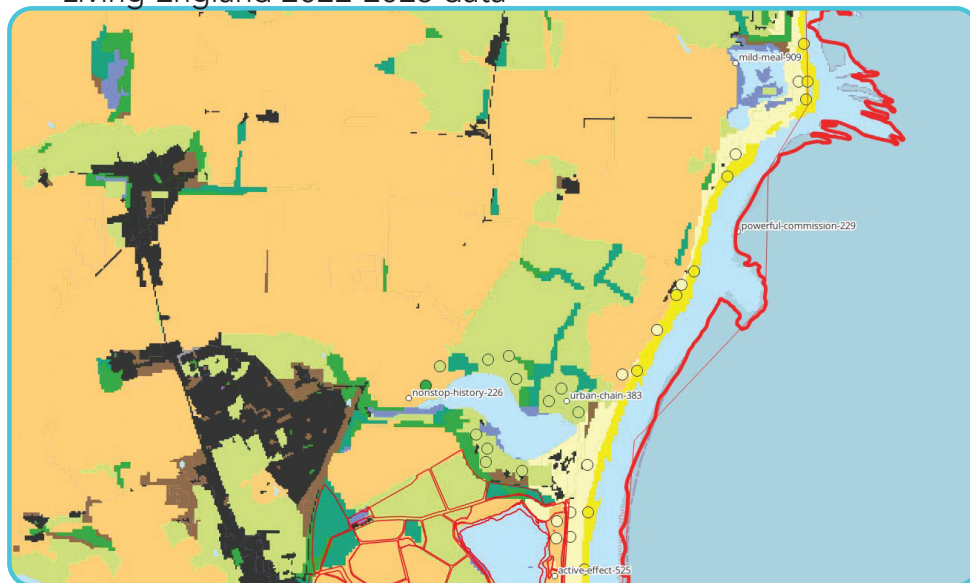
Deep Time data



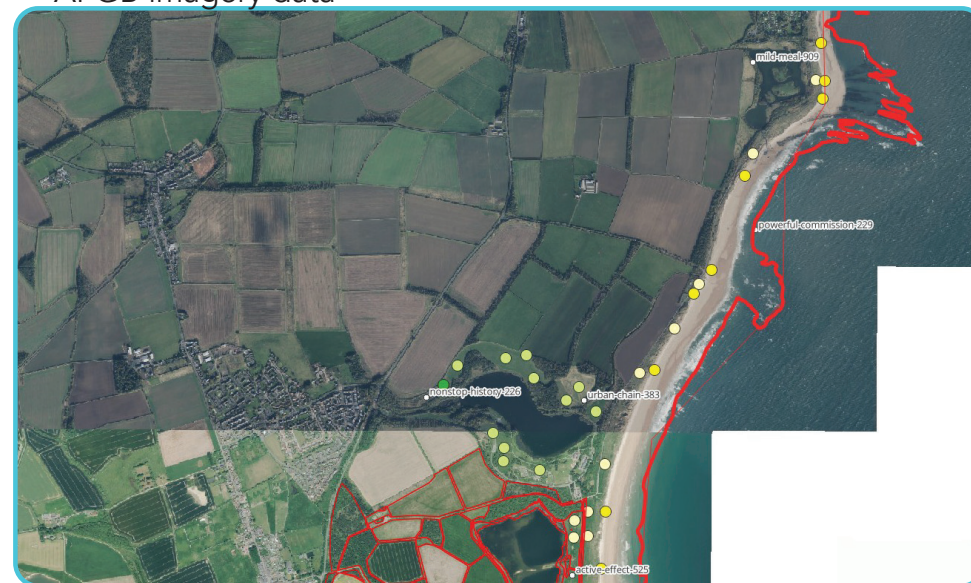
Phase IV data



Living England 2022-2023 data



APGB imagery data



Grids:
mild-meal-909
 powerful-commission-229
 nonstop-history-226
 urban-chain-383
 active-effect-525

33 LE data points total.
 25 match DT data, LE23
 has 26, PIV matches 23.

Deep Time data



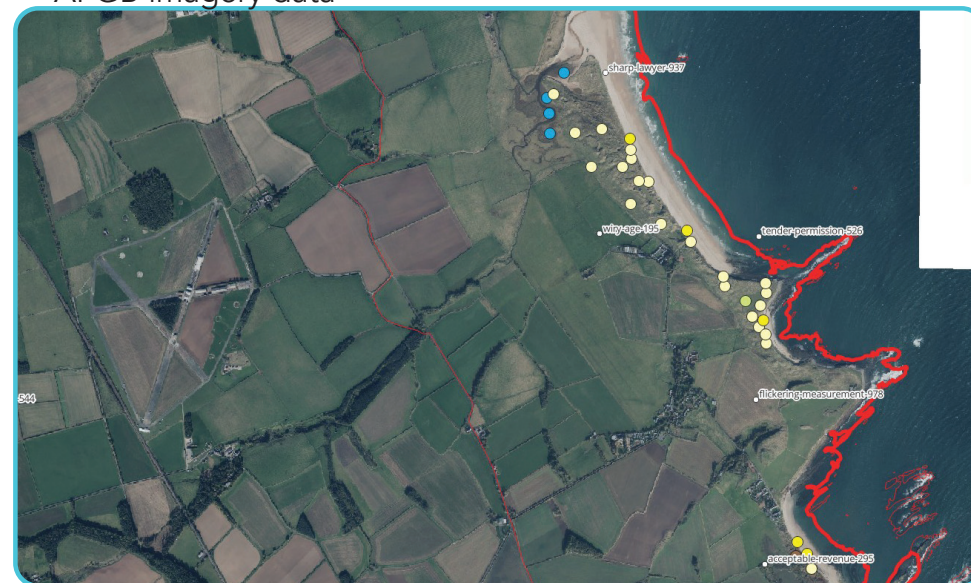
Phase IV data



Living England 2022-2023 data



APGB imagery data

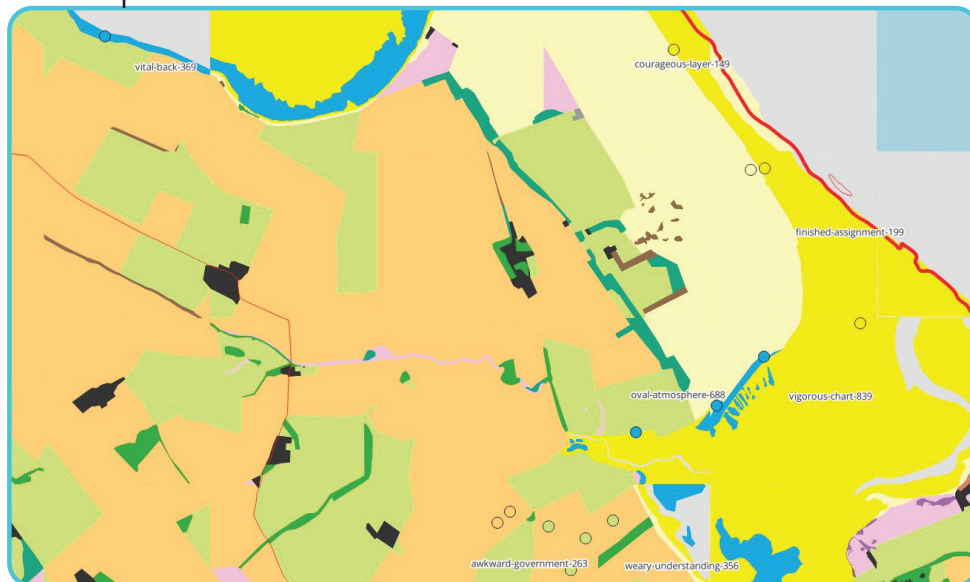


Grids:
sharp-lawyer-937
 wiry-age-195
 tender-permission-526
 flickering-measurement-978
 acceptable-revenue-295

35 LE data points total.
 29 match DT data, LE23
 has 32, PIV matches 31.
 A polygon incorrectly labelled as 'salt marsh'
 for DT negatively impacted the score.

App A: M5-4 - Northumberland Coast NL: detailed results 4.

Deep Time data



Phase IV data



Living England 2022-2023 data



APGB imagery data



Grids: **vital-back-369**, courageous-layer-149, finished-assignment-199, vigorous-chart-839, oval-atmosphere-688, weary-understanding-356, awkward-government-263

16 LE data points total.
11 match DT data, LE23
has 6, PIV matches 9.

Figure 19 - Mission 5, Northumberland Coast NL: detailed results 5.

Appendix B: M1 - Quality Assessment methodology for NPNL Mission 1

The squares are assessed both at an individual polygon level (Fidelity and Accuracy) and at the grid square level (Completeness).

Fidelity - does the polygon drawn represent a water body within the correct NPNL definition?

- 1 - yes it's a NPNL appropriate water body
- 0 - no it is not an NPNL appropriate water body

A percentage score is given for the grid square based on how many polygons drawn were correctly identified water out of the total number of polygons drawn

Accuracy: Is the polygon drawn correctly according to NPNL requirements

- 0: scored a zero in Fidelity
- 1: is on the water body but either misses some of the water or uses too few vertices
- 2: is on the water body but follows mapping layers other than the satellite
- 3: is on the water body but doesn't capture the maximum extent
- 4: captures the maximum extent of the water body and uses enough vertices to represent the contours of the shape well

A percentage score is given based on points scored out of the total possible points for the square

Completeness: Have all the water bodies in the square been identified?

- 1 - given for a polygon mapping water
- 0 - given for a water body that hasn't been mapped

A percentage score is given for the square based on how many of the total possible water bodies were identified.



Appendix C- North Pennines National Landscape quality assessment scoring table

Random ID	Deep Time grid name	NPNL QA by (initials)	Benchmark	Fidelity	Accuracy	Completeness
934408	slim-car-411	AM	100	0	0	0
933915	each-essay-691	AM	100	100	25	100
933338	ambitious-entry-828	AM	100	50	12.5	100
934619	unfolded-east-293	AM	100	100	100	100
934215	trim-method-363	AM	100	100	25	66.66666667
932340	prime-variety-552	AM	100	100	75	100
934166	mild-profession-415	AM	100	28.57142857	17.85714	66.66666667
934004	present-horse-282	AM	100	100	100	100
933836	troubled-reading-792	AM	100	70	70	100
933370	overjoyed-tennis-473	AM	100	100	100	100
934276	fatherly-while-514	AM	100	100	100	100
935045	self-reliant-request-760	AM	100	100	100	100
935238	known-hell-910	HB	100	100	87.5	100
933081	generous-midnight-571	HB	100	0	87.5	100
934152	monthly-mixture-196	HB	100	100	89.3	50
934540	bountiful-cousin-472	HB	100	100	100	66.6
932403	metallic-friendship-424	HB	100	100	100	100
933648	spectacular-tool-234	HB	100	100	100	82
933187	mountainous-finding-890	HB	100	100	100	100
932743	drafty-score-297	HB	100	100	100	100
932925	interesting-detail-227	HB	100	100	100	0
933697	grave-delivery-475	HB	100	100	100	100
934736	queasy-river-511	HB	100	92.8	92	35
932604	definite-currency-667	HB	100	0	0	0
932274	slow-collar-476	HB	100	100	100	100
933950	supportive-respect-182	HB	100	100	100	100
934854	muted-diamond-489	HB	100	100	100	100
934155	classic-lock-209	AL	100	100	100	100
932154	enormous-plant-231	AL	100	100	62.5	100
934706	incompatible-explanation-946	AL	100	100	100	100

935063	pristine-unit-748	AL	100	23.91304348	20.65217	100
932599	downright-item-866	AL	100	100	100	100
932855	waterlogged-selection-151	AL	100	100	100	100
932621	dutiful-refrigerator-999	AL	100	100	25	100
933384	outgoing-medicine-527	AL	100	100	100	100
933171	grandiose-dress-985	AL	100	100	100	100
933466	grandiose-delivery-845	AL	100	0	0	0
934676	profuse-warning-576	AL	100	100	100	100
932349	greedy-design-379	MW	100	100	100	100
932727	cute-bowl-894	MW	100	100	25	100
933704	decent-initiative-688	MW	100	100	100	100
934774	submissive-bunch-604	MW	100	100	100	100
933682	awful-manner-307	MW	100	100	75	100
935231	nifty-share-872	MW	100	100	100	100
932529	peppery-agreement-444	MW	100	0	0	0
934158	forsaken-warning-685	MW	100	100	100	0
934979	distant-page-171	MW	100	100	33.33333	85.71428571
934467	beneficial-lesson-856	MW	100	100	78.125	66.66666667
935241	extroverted-week-805	MW	100	100	100	100
932285	conventional-net-537	MW	100	100	100	100
Total			5000	4265.284472	3801.268	4119.314286
Percentage				85.30568944	76.02535	82.38628571

Appendix D - List of habitats identified

1. Acid, Calcareous and Neutral Grassland or Unimproved Grassland
2. Arable and Horticultural
3. Bare Ground
4. Bare Sand
5. Bog
6. Bracken
7. Broadleaved, Mixed and Yew Woodland
8. Built-up areas and Gardens
9. Coastal Saltmarsh
10. Coastal Sand Dunes
11. Coniferous Woodland
12. Dwarf Shrub Heath
13. Fen, Marsh and Swamp
14. Improved Grassland
15. Scrub
16. Water

Appendix E - Pre-participation survey questions

My Availability for Training and Missions

Which of the following missions are you available to join once you complete training? You can join as many as you like, but please only select the ones that you are likely to be available for.

- ☐ **September 2024 - Mission 1 (North Pennines National Landscape) ***
- ☐ **October 2024 - Mission 2 (Hadrian's Wall Corridor) ***
- ☐ **November 2024 - Mission 3 (Wallington Estate) ***
- ☐ **December 2024 - Mission 4 (Brightwater County Durham) ***
- ☐ **January 2025 - Mission 5 (Northumberland Coast National Landscape) ***

How many hours are you able to commit per week to training and any missions you later join? Whether you do it in small chunks or all in one sitting, previous participants mostly say that 2-4 hours per week is needed to really get into it and have the most satisfying experience.

- ☐ **1-2 hours**
- ☐ **2-4 hours**
- ☐ **4-8 hours**
- ☐ **8+ hours**
- ☐ **Not sure**

My Location

What is your postcode or zip code? *

Do you live within 25km of any of our mission landscapes? *

My Motivation

Do you have a particular preference for any one of our upcoming missions? *

Why do you say this about your preference? *

Which of the following best describes your answer about your preference? *

What are you most looking forward to about taking part in Deep Time? *

My Understanding of Nature Recovery and Climate Change

How much do you currently know about different habitats around the UK? *

How much do you currently know about how different landscapes, habitats, and archaeological sites around the UK are being affected by climate change? *

How much do you currently know about what's needed to make landscapes, habitats, and archaeological sites around the UK more resilient to climate change and meet net zero goals? *

As an individual, do you feel like there is much you can do to make a difference to climate change, other than through lifestyle choices like reducing energy consumption? *

My Sense of Place

I have a strong sense of place or connection with where I live *

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly agree

I have a strong sense of place or connection with one of the mission areas *

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly agree

Which mission areas do you have a strong sense of place or connection with?

- ☐ North Pennines *
- ☐ Wallington *
- ☐ Brightwater Landscape (Co. Durham & Darlington Borough) *
- ☐ Hadrian's Wall Corridor *
- ☐ Northumberland Coast *
- ☐ Northumberland generally *
- ☐ None *

Have you ever helped or volunteered with any of the project partners before? Tick all that apply

- ☐ DigVentures *
- ☐ National Trust *
- ☐ Durham Wildlife Trust *
- ☐ Northumberland Wildlife Trust *
- ☐ North Pennines National Landscape *
- ☐ Northumberland Coast National Landscape *
- ☐ Natural England *
- ☐ No - I have never volunteered or helped one of the partners before *

Year of birth *

Please select

Preferred pronouns *

Please select

Occupation *

Which of these categories best describes that occupation?

Please select

Ethnic origin *

Which of the following best matches what you consider your ethnic origin to be?

Please select

Country of residence *

Please select

Do you have any long-standing illness, disability, or infirmity? *

Please select

Why do you want to be a Futureonaut on the Deep Time mission? *

Which if these options best describes your previous answer?

Please select

Have you ever done any other citizen science or nature recovery activities before? *

Please select

Submit

Appendix F - Deep Time post-training survey questions

What is your current level of climate anxiety? *

- ☐ Not anxious
 - ☐ A little bit anxious
 - ☐ Somewhat anxious
 - ☐ Very anxious
-

Has involvement in the Deep Time training course impacted your levels of climate anxiety? *

- ☐ No
 - ☐ Yes - I'm a lot less anxious
 - ☐ Yes - I'm a little less anxious
 - ☐ Yes - I'm a little more anxious
 - ☐ Yes - I'm a lot more anxious
-

Do you undertake any of these active measures already to help with climate anxiety?

(Please check all that apply)

- ☐ Join climate action communities or projects (Deep Time counts!) *
- ☐ Make small daily eco-friendly changes. *
- ☐ Choose sustainable products and services. *
- ☐ Volunteer for environmental causes. *
- ☐ Advocate for policy changes. *
- ☐ Spread awareness to friends and family. *
- ☐ Practice self-care and connect with nature. *
- ☐ Other *
- ☐ None *

If you included 'Other' in your answer please tell us what other measures you use (optional)

As a result of my participation in Deep Time training...

(Please check all that apply)

- ☐ I feel less hope about the future due to climate change *
 - ☐ I feel more hope about the future now that I've been part of a climate action project *
 - ☐ It didn't affect my emotions around the impact of climate change *
 - ☐ I am more interested in how climate change affects my local place *
 - ☐ I feel inspired to participate in more climate action projects *
 - ☐ None of the above *
-

Do you have anything else you would like to tell us? (optional)

Appendix G - Deep Time post-project survey questions

Part 1. Your overall experience as a Cadet, Futureonaut or Mission Leader

* 1. Which is the highest Deep Time badge you've achieved?

- ☐ Cadet
- ☐ Futureonaut
- ☐ Mission Leader

* 2. How many hours a week did you spend on Deep Time?

- ☐ 0-2
- ☐ 2-4
- ☐ 4-10
- ☐ 10-20
- ☐ 20-30
- ☐ 30+

* 3. How do you rate the Deep Time experience as a way to do the following?

	Very poor	Poor	Neutral	Good	Very good
Learn more about the environment	☐	☐	☐	☐	☐
Get involved in nature recovery	☐	☐	☐	☐	☐
Make a valuable contribution to science	☐	☐	☐	☐	☐
Learn new skills	☐	☐	☐	☐	☐
Make a valuable contribution to climate change mitigation	☐	☐	☐	☐	☐
Gain confidence in your own abilities	☐	☐	☐	☐	☐
Get support and encouragement	☐	☐	☐	☐	☐
Have fun and connect with new people	☐	☐	☐	☐	☐

4. What did you most enjoy about participating in Deep Time?

* 5. How likely are you to take part in future Deep Time missions?

- ☐ Very unlikely
- ☐ Unlikely
- ☐ Not sure
- ☐ Likely
- ☐ Very likely

6. Why is this?

* 7. If you stopped taking part at any point (or never started), why was this?

- ☐ I didn't stop!
- ☐ I didn't intend to participate in all 5 missions
- ☐ Life events or health issues got in the way
- ☐ Parts of it were too difficult for me
- ☐ It was too time consuming
- ☐ It was too frustrating
- ☐ I lost interest
- ☐ It felt like I lost momentum
- ☐ It wasn't what I expected

Other Comments

* 8. How important was the Deep Time community and the ability to connect with others to your participation

It was detrimental (I found the social interaction aspect challenging)	Not important (I would be happy to work by myself)	Neutral	Somewhat important (I occasionally appreciate the ability to use the chat)	Very important (The community is a key factor in my participation)
☐	☐	☐	☐	☐

*** 9. We want to understand how successful we are in engaging and training people with differing abilities to learn and participate in citizen science and how we might attract and maintain a wider audience.**

Do you identify as having any physical or mental conditions or illnesses that affect your ability to carry out day-to-day activities?

- ☐ Yes
- ☐ No
- ☐ Prefer not to say

10. If yes, do these conditions affect you in any of the following areas?

- ☐ Vision (for example, partial blindness or partial sight)
- ☐ Hearing (for example, deafness or partial hearing)
- ☐ Mobility (for example, walking short distances or climbing stairs)
- ☐ Dexterity (for example, lifting and carrying objects, using a keyboard)
- ☐ Learning or understanding or concentrating
- ☐ Memory
- ☐ Mental Health
- ☐ Stamina or breathing or fatigue
- ☐ Socially or Behaviourally (for example associated with autism spectrum disorder, which includes Asperger's and attention deficit hyperactivity disorder)
- ☐ Other (please specify)

11. How could we improve the accessibility of Deep Time for you personally?

Part 2. What you got out of taking part

We have been measuring your feelings about Deep Time at different points in the process to help us understand our impact. Let us know how you feel at the end of the journey.

* 12. Please rate the following statements

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
My understanding of the impact of climate change on different landscapes and archaeological sites around the UK has increased	☐	☐	☐	☐	☐
My understanding of how habitat mapping can help us tackle climate change, achieve Net Zero goals or make landscapes more resilient has increased	☐	☐	☐	☐	☐
My knowledge of different habitats around the UK has increased	☐	☐	☐	☐	☐
My sense of place or connection to the study area has increased	☐	☐	☐	☐	☐
My sense of place or connection to where I live has increased	☐	☐	☐	☐	☐
My interest in the environment or nature recovery has increased	☐	☐	☐	☐	☐
My interest in citizen science has increased	☐	☐	☐	☐	☐

* 13. As a result of my participation in Deep Time...

	Significantly decreased	Slightly decreased	Remained the same	Slightly increased	Significantly increased
My anxiety about the potential effects of climate change on my life has	☐	☐	☐	☐	☐
My confidence in the ability of my actions to make a positive difference in the climate emergency has	☐	☐	☐	☐	☐

* 14. Has Deep Time inspired you to make further daily changes ?

- ☐ Yes, I have joined other action communities or projects
- ☐ Yes, I have made more small daily eco friendly changes
- ☐ Yes, I chose even more sustainable products and services
- ☐ Yes, I have started volunteering for environmental causes
- ☐ Yes, I have begun to advocate for policy change
- ☐ Yes, I have started to spread awareness to friends and family
- ☐ Yes, I have begun to practice self care and connect more with nature
- ☐ No, I already did as much as I was able
- ☐ No, I did not feel inspired to do more
- ☐ Other (please specify)

* 15. Have you become involved with other nature recovery projects as a result of your participation in Deep Time?

- ☐ No
- ☐ Yes (please let us know which)

16. Is there anything else you've found valuable or rewarding or learned while taking part?

Part 3. What would you change or improve?

17. Where did you most need more training, support, or guidance?

18. What problems did you encounter while using the Deep Time Map Portal? Were they resolved to your satisfaction?

19. What features or functionality could we add to make the platform better?

20. Do you have any other suggestions for how we could make it easier or more rewarding for more people to take part in future Deep Time missions?

21. Is there anything else you want to tell us that could help us to develop future Deep Time missions?

Part 4. How should the data be managed?

We are investigating ways we might use the Deep Time data. Please rate the following statements to help us understand you feel about the future of the dataset you helped to create.

22. I believe Citizen Scientists should have a say in the way that the data they contribute is used and distributed beyond its initial use.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
☐	☐	☐	☐	☐

* 23. I feel comfortable with the data I contributed being used by DigVentures and the partner organisations of the Citizen Science Local Pilots project.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
☐	☐	☐	☐	☐

* 24. I would feel comfortable with the data I contributed being distributed to other interested parties beyond the Citizen Science Local Pilots project

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
☐	☐	☐	☐	☐

* 25. I would feel comfortable with the data I contributed being used by DigVentures and the CSLP partner organisations for new nature recovery projects

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
☐	☐	☐	☐	☐

* 26. I would feel comfortable with the data I contributed being distributed to other interested parties for new nature recovery projects.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
☐	☐	☐	☐	☐

* 27. I would feel comfortable if DigVentures and the CSLP partner organisations used the data I contributed to train an AI.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
☐	☐	☐	☐	☐

* 28. I would feel comfortable if the data I contributed was distributed to other interested parties in order to train an AI

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
☐	☐	☐	☐	☐

* 29. I would like my individual data contribution to be credited

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
☐	☐	☐	☐	☐

Part 5. Continuing your Deep Time journey

* 30. How likely would you be to get involved with the following activities?

	Extremely unlikely	Unlikely	Neutral	Likely	Extremely likely
In habitat focussed missions	☐	☐	☐	☐	☐
In habitat focussed ground survey (in person)	☐	☐	☐	☐	☐
In archaeology focussed missions	☐	☐	☐	☐	☐
In archaeology focussed ground survey (in person)	☐	☐	☐	☐	☐

Thank you for your feedback!

31. Please provide your email if you would be happy to be contacted about your feedback.