Nature-based solutions for climate change adaptation and water pollution in agricultural regions: services supporting the synthesis and dissemination of results

Final report deliverable D2

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List of abbreviations

BS	Buffer strip
BS-R	Buffer strip for surface runoff interception
BS-G	Buffer strip for subsurface groundwater interception
CW	Constructed wetland
FWS	Free water surface constructed wetland
GAI	Global aridity index
GDP	Gross Domestic Product
HF	Horizontal subsurface flow constructed wetland
HLR	Hydraulic loading rate
HRT	Hydraulic retention time
NBS	Nature-Based Solutions
NBS A	NBS for Manure-derived wastewater and sludge
NBS B	NBS as landscape elements for diffuse sources of pollution
NBS C	NBS as landscape elements for water retention and resilience to climate change
MAR	Managed aquifer recharge
MCA	Multi-criteria analysis
MCorA	Multi Correspondence Analysis
PPP	Purchasing Power Parity
SF	Surface flow constructed wetland
SSF	Subsurface flow constructed wetland
VDD	Vegetated Drainage Ditch
VF	Vertical subsurface flow constructed wetland
VT	Value tranfer

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1 INTRODUCTION AND METHODOLOGY

1.1 Selection of NBS

The Nature-based solutions (NBS) were selected for the three broad categories (hereinafter referred as **issues** in the contracting activities) defined in the technical specification of the tender:

— NBS A: Treatment of manure-derived wastewater and sludge before application as fertilizer. The main purpose of the NBS in this category is the control of nutrient surplus, veterinary/human pharmaceuticals and other contaminants.

— NBS B: Landscape elements addressing diffuse sources of pollution due to fertilizers (and associated contaminants) and/or pesticides; unlike the previous category, in this case the landscape elements are "passive" (i.e. the natural processes they support are not man-managed) and treat input flows which are not precisely identified a priori, depending on the landscape, climate and fertilizer/pesticide application on the fields. The main purpose of the NBS in this category is diffuse pollution control (nutrients, pesticides, sediments).

— NBS C: Landscape elements addressing water retention to sustain water availability during dry periods, and contribute to resilience against climate change. The main purpose of the NBS in this category is to support water supply during dry periods/summer, and/or flood mitigation.

The preliminary list of NBS for the three categories (**Table 1**) was selected on the basis of:

— The **Natural Water Retention Measures (NWRM)** website (nwrm.eu), from which only actual NBS were selected, neglecting many listed solutions, which can be better defined as Best Management Practices in the agricultural sector (such as crop rotation, intercropping, or no till agriculture)

— **Relevant literature studies**

Table 1. Preliminary list of identified NBS

NBS category	NBS type	Key references for NBS definition
A: Manure-derived wastewater and sludge	1. Constructed wetlands (CWs) (a) Horizontal subsurface flow (HF) (b) Vertical subsurface flow (VF) (c) Free water surface (FWS) (d) Aerated wetlands 2. Waste stabilization ponds (WSP) or lagoons (a) Anaerobic ponds (AP) (b) AP + Facultative ponds (FP) (c) AP + FP + Maturation ponds (MP) (d) Aerated ponds	Estrada and Hernandez (2002) Hunt et al. (2002) Kadlec and Wallace (2009) Knight et al. (2000) Meers et al. (2008) Vidal et al. (2018)
B: Landscape elements for diffuse sources of pollution	1. Wetlands (a) In-line (nutrients, pesticides, sediments)	nwrm.eu Acreman and Holden (2013) Barling and Moore (1994)

NBS category	NBS type	Key references for NBS definition
	(b) Off-line (nutrients, pesticides, sediments) 2. Vegetated drainage ditches (VDD) (a) Without hydraulic control structures (b) With hydraulic control structure 3. Buffer strips (a) For surface water (runoff – BS-R) (b) For subsurface water (groundwater – BS-G) (c) Integrated buffer zones	Castaldelli et al. (2015) Collins et al. (2009) Cooper et al. (2004) Dollinger et al. (2015) Hansen et al. (2016) Hickey and Doran (2004) Jordan et al. (2003) Kadlec and Wallace (2009) Kröger et al. (2013) Kumwimba et al. (2018) O'Geen et al. (2010) Stutter et al. (2012) Vidon et al. (2019) Vymazal, J. and Březinová (2015)
C: Landscape elements for water retention and resilience to climate change	1. Droughts/Storage (a) Farm (Storage) Ponds (b) Storage Wetlands - Marshes storage (c) Infiltration Ponds (MAR – Managed aquifer requarge) (d) Infiltration Wetlands-Marshes (MAR) (e) Infiltration Wood (MAR) (f) Dry infiltration areas (MAR) 2. Flood (a) In-line Detention basins (b) Off-line Detention basins	nwrm.eu Acreman and Holden (2013) Ameli and Creed (2019) Berg et al. (2016) Brader et al. (2013) Camnasio and Becciu (2011) Cohen et al. (2016) Dillon (2005) Dillon et al. (2019) Dowing (2010) Fiener et al (2005) Gleason et al. (2007) Golden et al. (2016) Ibrahim and Amir-Faryar (2018) Lane et al. (2010) Lane et al. (2018) Leon et al. (2018) Morris et al. (2008) Thorslund et al. (2017) Tiner (2003) UN-Water (2018) Wisser et al. (2010)

1.2 Attributes for landscape, climate, and sizing

The relevant attributes in terms of landscape, climate, and sizing were separately identified for the three typologies of NBS (A, B, C) of table 1. The lists are reported in Annexes and were used as a starting point to build the necessary datasets.

After and in function of the evidence gathered from literature, the following **characteristics will be defined for each attribute in the next sections**:

— Unit in case of ordinal descriptors (e.g. ha, m^3, tonN/y)

— Type in case of cardinal descriptors (e.g., binary, categorical)

— Descriptors used to define the suitability constraints

— Descriptors used to build the cause-effect relationships

1.3 Attributes for benefits

We hereinafter define **benefit** (J) each objective that can be linked to the previously defined descriptors (landscape, climate, sizing) by a cause-effect relationship. This means that, from a logical point of view, both the primary benefit and the side-benefits need to be managed in a similar way. Several recent publications have highlighted the capability of NBS to be multipurpose, i.e. to provide several benefits with a single solution (UN 2018; Raymond et al., 2017). However, it is also clear that not all NBS benefits can be maximized, often leading to a priorization of NBS benefits according to main and side-objectives (Calliari et al., 2019). Accordingly, the main and side benefits for each NBS issue were defined as follows:

- Main benefit (J_M): a benefit directly related to the issue that the NBS is expected to respond to (e.g. nitrogen removal for a NBS A for manure-derived wastewater and sludge);
- Side benefit (J_S): a benefit provided by a NBS additional to the main benefit, i.e. considering a NBS as a multipurpose design element (e.g. amenity attractiveness of a NBS C for water retention)

The distinction between main and side benefits is relevant when considering the expected products of the work:

- Favourability map, which will be built for each NBS considering only J_M, i.e. without the spatial multi-criteria analysis (MCA);
- Opportunity map, which will be built considering both J_M and J_S based on spatial MCA with weights.

The relevant benefits were separately identified for the three issues.

Similarly to descriptors, the lists are reported in Annexes and were used as tentative lists to build the dataset.

After and in function of the evidence gathered from literature, the following **characteristics will be defined for each benefit in the next sections**:

— Unit in case of ordinal descriptors (e.g. tonN/y/ha)

— Type in case of cardinal descriptors (e.g., binary, categorical)

Finally, it's worth to be noted that the organization of the work, thinking in terms of mono-objective (main benefit vs. side benefit) when dealing with multi-purpose NBS, led to have similar NBS with similar benefits, but managed differently according to the different issues. An example are wetlands, which have attributes of both water quality (e.g. N abatement) and water quantity (storage water volume), but are inverted between main and side benefits depending on the NBS issue, B (diffuse pollution) or C (flood and drought).

2 NBS RELATIONSHIPS

The chapter aims to summarise the development of a statistical meta-analysis or research synthesis with the goal of deriving three types of **relationships**:

- Relationships for effectiveness, i.e. relationships between the dimensional parameters of each solution (e.g. area, volume), landscape and climate (e.g. topography, temperature) and effectiveness (e.g. nutrient retention);
- Relationships for costs, i.e. relationships between the dimensional parameters of each solution (e.g. area, volume), and region-specific implementation costs;
- Relationships for benefit monetization, i.e. relationships for the evaluation of direct and indirect benefits through value transfer approaches.

2.1 Building of relationships for effectiveness

Relationships for effectiveness are defined as *"Relationships between the dimensional parameters of each solution (e.g. area, volume), landscape and climate (e.g. topography, temperature) and effectiveness (e.g. nutrient retention)"*.

Two approaches were used to build relationships (a):

- **statistically-based**, building the equations on the basis of a Multiple Correspondence Analysis and a multiple linear regression analysis
- **expert-based**, through the definition of either simplified process-based equations[1] or value functions (Alacron et al., 2010)[2]

2.1.1 Statistical relationships

2.1.1.1 Methodology

The purpose of statistical relationships is to support the development of "favourability" and "opportunity" maps, i.e. plotting for each type of Nature Based Solution (NBS) the value of an index expressing the benefits accruing to this NBS type (with a reference, unit sizing to be spatially comparable). These benefits are in principle a multidimensional vector within which certainly one key element is present: the abatement efficiency of different pollutants.

An Excel database was created which collected about a hundred experiences described in scientific papers that detail the characteristics of the implemented NBS in terms of landscape, climate and design and the corresponding abatement efficiency (%) of the considered contaminants, following summarized for each NBS investigated

- NBS A: TN, TP, TKN, BOD_5, COD, TSS
- NBS B
    - FWS: TN, N-NO3, TP, P-PO4

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[1] Despite the use of simplified assumptions, these equations remain process-based, since they estimate the performance of specific processes, such as water storage or C sequestration.

[2] Defining the value function requires measuring preference, or the degree of satisfaction produced by a certain alternative option for a measurement variable (indicator). Each measurement variable may be given in different units; therefore, it is necessary to standardise them into units of value or satisfaction, which is basically what the value function does. The method proposed rates satisfaction on a scale from 0 to 1, where 0 reflects minimum satisfaction (Smin) and 1 reflects maximum satisfaction (Smax).

To determine the satisfaction value for an indicator a few preliminary steps have to be guaranteed (Alacron et al., 2010):

- Definition of the orientation (increase or decrease) of the value function.
- Definition of the points corresponding to the minimum (Smin, value 0) and maximum (Smax, value 1) performance/satisfaction.
- Definition of the kind (ordinal or cardinal) and of the shape (linear, concave, convex, S-shaped) of the value function.
- Definition of the mathematical expression of the value function

- BS-R: TP, P-PO4, TN, N-NO3, Sediments, TSS
- BS-G: N-NO3

The dataset was screened to limit "gaps" in the information as much as possible, which led to discard the sample in the statistical analysis. Therefore, a **sub-dataset** was developed dedicated to statistical analysis. These sub-datasets are visible in attachment: NBS A, wetlands for manure-driven wastewater (Attachment 1); NBS B, VDDs and wetlands (Attachment 2); NBS B, buffer strips (Attachment 3).

Two statistical tools were used and combined to analyze the dataset: (i) Multi Correspondence Analysis; (ii) multiple linear regression analysis.

A preliminary step was to identify which are the most and least significant variables, thus reducing the problem complexity, while verifying whether the data spontaneously collected amongst meaningful clusters. To this aim, rather than a Principle Component Analysis, the **Multiple Correspondence Analysis** (MCorA, e.g. Abdi and Williams, 2010) was adopted, as several descriptors are naturally categorical. The SPSS software[3] was used.

This step provided an interesting added value which was a qualitative comprehension of the behavior of the available experiences and gave a preliminary indication of which variables are not expected to convey added value and, in principle, might be neglected. Indeed, it was expected that the variables that show to have a low differentiation power in this analysis (and are hence discarded) would do the same in the next step of searching for quantitative multiple regression relationships.

Subsequently, a quantitative relationship between abatement efficiency and NBS characteristics is obtained by means of a **multiple linear regression analysis**. In doing so, the results of MCorA were taken into account by developing a version in which the variables that the previous MCorA step had identified as not significant were neglected. This allowed to reduce the dimensionality of the problem, which was fundamental, due to the scarcity of data compared to the high number of descriptors. However, as there are structural differences in the two approaches[4], the version including these variables was also analyzed in parallel and the results are compared. The procedure was doubled, adding or removing the loading rates from the regression analysis. Consequently, the multiple linear regression analysis provided four linear models:

— (1) multiple linear regression with variables selected by MCorA, without the influent loads;

— (2) multiple linear regression with variables selected by MCorA, with the influent loads;

— (3) multiple linear regression with all variables, without the influent loads

— (4) multiple linear regression with all variables, with the influent loads.

This whole procedure was repeated for the three NBS for which it was possible to set up a significant dataset (NBS A, wetlands for manure-driven wastewater; NBS B, VDDs and wetlands; NBS B, buffer strips) and for each pollutant of interest.

The multiple linear regression models were evaluated with both statistical goodness of fit indexes and expert-based evaluation.

The **goodness of fit indexes** used to evaluate the multiple linear regression models were:

— R2: coefficient of determination, i.e. the fraction of the variance of the dependent variable (in this case the abatement efficiency) is predictable from the independent

[3] IBM SPSS statistics 23: https://www.ibm.com/support/pages/downloading-ibm-spss-statistics-23

[4] The variables expected to have a greater effect on NBS performance can vary between MCorA and multiple linear regression analysis. This is due to the following reasons: i) the two MCorA dimension do not explain 100% of the variability; and ii) there is a structural switch between the two analysis: the continuous variables are discretized in MCorA, while for the categorical variables, in the linear regression analysis, each category has to be transformed into a binary "dummy" variable (which requires limiting the number of variables owing to the overall paucity of data). For this reason, a parallel analysis was developed: with and without the MCorA discarded variables.

variables (the higher, the better; if negative, the trivial model always set equal to the observation mean is preferable)

- R2 adjusted: a version of R2 corrected to consider the fact that while including more regressors (independent variables, i.e. descriptors), obviously the performance of R2 improves, but the model is weaker because it is built on a smaller dataset (the higher, the better)
- RMSE: Root Mean Square Error, i.e. the sum of the "model-observation" squared errors (the lower, the better)
- DoF model: number of estimated parameters (excluding the intercept)
- DoF residuals: number of "free" observations used for the estimation (i.e. total number of data, minus the number of parameters, minus 1 for the intercept)
- Obs./parameters: number of observations per estimated parameter (the higher, the better; ideally it should be greater than 10).

Subsequently, an **expert-based evaluation**[5] was performed to verify the significance of the variables selected by the multiple linear regression analysis. Moreover, experts chose the most appropriate linear cause-effect model for the favourability and opportunity maps for each NBS and each pollutant, balancing both the results of statistical indexes and the significance of the selected variables[6].

If the **expert-based evaluation was positive**, the selected multi regression linear model are proposed to predict pollutant removal performance for the development of the favourability and opportunity maps, estimating the expected effect on the performance of relevant climate, landscape, and design variables.

If the **expert-based evaluation was negative**, the median value from the frequency density function are proposed to predict the pollutant removal performance, equal for all EU regions. The effect of climate, landscape, and design variables will be considered in the favourability and opportunity map methodology by defining a set of suitability criteria based on literature evidence and on expert evaluation.

For sake of simplicity, the statistical analysis considered only linear regression models, avoiding testing other non-linear fittings (e.g., lognormal, exponential). The rationale for this choice is exposed in the following: (i) the aim of this analysis was to identify variables and predictive models that could potentially affect removal performance of NBS at EU scale and, at the same time, maintain reliability against literature and designer expertise; (ii) the selected models should not be used for design purposes, but just to interpret the statistical variability of the dataset developed for each NBS and each pollutant at European scale; (iii) the selected linear models presented SD residuals in the range of ± 20%, which were considered acceptable for the large scale EU map; (iv) the performance of the selected models were also compared with the estimation of well-known benchmark models, showing a better representation of the removal efficiency collected in the dataset (see section, 2.1.1.6). As a consequence of the previous methodological steps, the linear models

[5] **Wetland and VDD experts**: Dr. Fabio Masi (IRIDRA, project manager of this study); Dr. Eng. Anacleto Rizzo (IRIDRA, co-author of this study).
Buffer strips experts: Dott. Giulio Conte (IRIDRA, co-founder of CIRF) and Eng. Andrea Nardini (CIRF) CIRF – Centro Italiano Riqualificazione Fluviale (Italian Centre River Restoration – www.cirf.org)

[6] Therefore, the selected model was chosen with an expert-based approach for each NBS and each pollutant, without prioritizing either the statistical goodness of fit indexes or the significance of the screened variables. In some cases, a model with slightly worse fitting performance was chosen because the selected variables were more appropriate; in other cases, even if the variables were significant, the model was not chosen due to too low fitting performance.

were judged suitable for the purposes of the study, therefore further efforts in testing different fitting models were considered not necessary, also because they could involve the risk of improper extrapolation removal performance if used with variables values outside the range collected in the dataset[7].

2.1.1.2 Model selection for NBS A

The detailed analysis of MCorA for NBS is reported in Annex 8. The multiple linear regression analysis was performed by regressing the abatement efficiency (for each of the 6 contaminants, i.e., Nitrogen N, Phosphorous P, Biochemical Oxygen Demand BOD, Chemical Oxygen Demand COD, Total Kjeldahl Nitrogen TKN, and Suspended Solids SS) on the candidate "causal factors", including the characteristics of the wetland NBS (**Table 2**).

The results of the analysis are reported in the following sub-sections.

Table 2. List of variables for multiple linear regression analysis of the NBS A dataset

Variable name	Variable Description
L_altit	Altitude
L_country	Country
C_avT	Average annual Temperature
C_n_cold	Average annual n of months with T < 6°C
C_p	Average annual precipitation - 1
C_AridIx	Global aridity index
C_PET	Potential annual evapo-transpiration (Global AI-PET)
C_REG	Biogeographical region
D_Type	Type
D_topoADJ	Topographic adjustment
D_Area	Area
D_ratio	Aspect-Ratio
D_depth	Average depth
D_veg	Type of aquatic vegetation
D_LoadTKN	Annual input load TKN
D_LoadN	Annual input load N
D_LoadP	Annual input load P
D_LoadSS	Annual input solids load
D_LoadCOD	Annual input COD load
D_LoadBOD	Annual input BOD5 load
D_Q	Water inflow

[7] Essentially, the dataset was considered not extended enough to safely test non-linear fitting models. Despite the limit of using only linear multiple regressions in terms of statistically fitting performance, this choice can be considered robust for the aim of the study. At EU level is less important if the performance could be slightly better with a better fitted non-linear model, since the residual from the linear model in the range of ± 20% can already be considered acceptable for the purpose of the study. On the other hand, it could be more risky to have a non-linear model giving unrealistic removal performance, if used with values of variables outside the range of values collected in the dataset used for fitting. The dataset is not extended enough, therefore, it could happen that the collected value of a variable does not cover all the variability expected at EU level. In such case, a linear model simply estimates the performance outside the variability of the range of the dataset neither increasing nor decreasing the expected trend in performance. Contrarily, a non-linear model would interpret the effect of a value outside the range of the dataset giving a "sort of judgement" simply based on fitting performance (e.g. an exponential model would increase the expected removal efficiency with a positive higher variable, instead a logarithmic model would decrease the expected value), a risk that was preferred to avoid.

Variable name	Variable Description
D_WWtype	Type of ww
D_PT	Primary treatment
D_dilu	Dilution
D_recirc	Recirculation
D_filling	Filling media
N_abat	Removal % TKN
N_abat	Removal % N
P_abat	Removal % P
S_abat	Removal % TSS
COD_abat	Removal % COD
BOD5_abat	Removal % BOD5

2.1.1.2.1 General considerations on the results of multiple linear regression analysis for NBS A and model selection

For all variables, except for phosphorous (P) and suspended solid (TSS), the load (loading rate variable) resulted not relevant.

Moreover, none of the variables discarded by the MCorA turned out to be significant in any of the cases, and therefore the final specification of the model remained unchanged (so columns 1 and 2 coincide with columns 3 and 4, respectively).

Generally speaking, there was heterogeneity among the variables that were found to be significant for the different contaminants; however, the sign of variables remained constant for all the model versions for a given contaminant.

The variables resulting more significant for more than one contaminant were:

— *Specific water inflow*: appears in 5 out of 6 cases, and when significant it has a negative sign (i.e. the higher it is, the lower the efficiency)

— *ww_mix_RNF*: appears in 4 cases, and in 3 cases it has positive sign (i.e. the higher it is, the higher the efficiency)

— *Previous treatment Primary NBS* + *Secondary NBS*: appears in 3 cases, and always has a negative sign (i.e. the higher it is, the lower the efficiency)

— *Previous treatment Primary NBS*: appears in 2 cases, always negative

— *Filling media Porous media + soil*: appears in 2 cases, always positive

— *Area*: appears only in 2 cases, always positive, and only in one case (P) is it significant; indeed, since the load variable is actually the specific loading rate (kg mass/ha/year) it was expected a priori that the Area would be not influent

— *Type of aquatic vegetation Emergent*: appears in 2 cases, always negative.

2.1.1.2.2 Selected model for TN removal of NBS A

All the models perform in a similar manner for TN removal in terms of statistical performance. **Model (3)** was chosen for the slightly higher R2 adjusted and because all the involved variables were found to be significant by the experts. Indeed, both positive and negative dependence on the selected variable are in accordance with literature on constructed wetlands (see Kadlec and Wallace, 2009). In particular, it can be noted that:

— the negative effect – i.e. lower TN removal % – of a higher specific water inflow is in line with the shorter hydraulic retention time of the system;

— the negative effect – i.e. lower TN removal % – in case of manure-driven wastewater mixed with agricultural runoff is in agreement with a lower expected concentration in this type of wastewater compared to a higher concentration when manure-driven wastewater is the only influent source of pollutants; since TN is known to be removed principally by biological processes in wetlands (Kadlec and Wallace, 2009; Vymazal 2007), lower concentrations are expected to reduce the removal performance of bacteria;

— a negative effect – i.e. lower TN removal % – is also expected when manure comes from poultry farms, since poultry is more difficult to treat than pig manure (indeed, fewer CW applications for poultry manure treatment are available in literature)

— the negative effect – i.e. lower TN removal % – if the NBS is a tertiary treatment (i.e. after a secondary treatment stage, either NBS or grey solution) is consistent with the lower expected influent concentrations in comparison to secondary NBS for manure-driven wastewater, for the same reasons explained for the mixture with agricultural runoff mentioned above;

— the positive effect – i.e. higher TN removal % – if the NBS includes porous media filling is also consistent, as it is a proxy of the use of additional media to improve performance, such as a hybrid CW with also subsurface flow systems;

NBS A – TN – Linear models	**(1)**	**(2)**	**(3)**	**(4)**
Goodness of fit indexes				
Observations	31	31	31	31
R2	0.666	0.667	0.695	0.696
R2 adjusted	0.583	0.566	0.603	0.585
DoF model	5	6	5	6
DoF residuals	24	23	23	22
RMSE	0.166	0.169	0.162	0.165
Obs./Parameters	4.43	3.88	4.43	3.88
Max residual (positive)	0.232	0.229	0.250	0.252
Max residual (negative)	-0.385	-0.380	-0.371	-0.373
SD residuals	0.148	0.148	0.141	0.141
Selected parameters				
Average annual precipitation cm/year	0.00182***	0.00189**	0.00154**	0.00150**
	(0.00062)	(0.00076)	(0.00056)	(0.00066)
Specific water inflow	-0.00019***	-0.00026	-0.00019***	-0.00015
	(0.00005)	(0.00022)	(0.00005)	(0.00019)
ww_mix_RNF	-0.28871***	-0.28334***	-0.28044***	-0.28317***
	(0.08289)	(0.08956)	(0.08617)	(0.09315)
ww_Poultry	-0.34942***	-0.34456***	-0.33049***	-0.33266***
	(0.04719)	(0.05295)	(0.04667)	(0.05354)
Previous treatment Primary NBS + Secondary NBS	-0.30760***	-0.30380***	-0.29820***	-0.30004***
	(0.04499)	(0.05223)	(0.04993)	(0.05617)
Filling media Porous media + soil	0.24325**	0.25054**	0.24817**	0.24431**
	(0.10593)	(0.11554)	(0.10613)	(0.11473)
Type of aquatic vegetation Emergent			-0.25072***	-0.25717***
			(0.04788)	(0.04489)
Total Nitrogen loading rate		0.00049		-0.00027

		(0.00151)		(0.00128)
Constant	0.48552***	0.47166***	0.75637***	0.77091***
	(0.08279)	(0.11555)	(0.08365)	(0.12201)

— the negative effect – i.e. lower TN removal % – when only emergent vegetation is planted in wetlands is also consistent, since, especially in FWS, a greater biodiversity is expected to improve the plant nitrogen uptake of the NBS.

Table 3. Detailed results of multiple linear regression for NBS A for TN. Heteroskedastic robust standard errors in parentheses. The selected statistical model is highlighted in red.

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.2.3 Selected model for TP removal of NBS A

Model (4) was chosen to simulate TP removal of NBS A, since it was the one with the best statistical performance in terms of R2 and SD residuals. Moreover, the expert judgment on the consistency of the selected variable was positive. Indeed, both positive and negative dependence on the selected variable are in accordance with literature on constructed wetlands (see Kadlec and Wallace, 2009). In particular, it can be noted that:

— the negative effect – i.e. lower TP removal % – when the NBS is a tertiary stage is consistent with the lower expected influent concentrations, in analogy with the model for TN removal;

— the negative effect – i.e. lower TP removal % – when only emergent vegetation is planted in wetlands is also consistent for the same reasons explained for the TN removal model;

— the negative effect – i.e. lower TP removal % – when phosphorous loading rate is higher can also be justified by lower hydraulic retention times, in line with the TN removal model;

— the positive effect – i.e. higher TP removal % – when the NBS area increases is also expected and properly captured by the model; indeed, P is mainly removed by sorption processes (adsorption, plant uptake) in wetlands (Kadlec and Wallace, 2009; Vymazal 2007), therefore, a larger NBS area means more adsorption sites and plants for uptake, and therefore, greater possibility of removing P

Table 4. Detailed results of multiple linear regression for NBS A for TP. Heteroskedastic robust standard errors in parentheses. The selected statistical model is highlighted in red.

NBS A – TP – Linear models	**(1)**	**(2)**	**(3)**	**(4)**
Goodness of fit indexes				
Observations	32	32	32	32
R2	0.153	0.261	0.369	0.494
R2 adjusted	0.0947	0.182	0.275	0.397
DoF model	2	3	3	4
DoF residuals	29	28	27	26
RMSE	0.247	0.235	0.221	0.201
Obs./Parameters	8.00	6.40	6.40	5.33
Max residual (positive)	0.405	0.497	0.409	0.474
Max residual (negative)	-0.389	-0.466	-0.389	-0.419
SD residuals	0.239	0.223	0.206	0.185

NBS A – TP – Linear models	(1)	(2)	(3)	(4)
Selected parameters				
Specific water inflow	-0.00019***	0.00009	-0.00026***	0.00008
	(0.00004)	(0.00016)	(0.00003)	(0.00016)
Previous treatment Primary NBS + Secondary NBS	-0.27364***	-0.34035***	-0.33531***	-0.39422***
	(0.06620)	(0.06481)	(0.04940)	(0.04851)
Area			0.42671***	0.36330***
			(0.11062)	(0.09915)
Type of aquatic vegetation Emergent			-0.38728***	-0.52466***
			(0.04592)	(0.07706)
Total Phosporous loading rate		-0.06308*		-0.07098**
		(0.03483)		(0.03289)
Constant	0.59157***	0.69872***	0.90698***	1.16845***
	(0.05120)	(0.07186)	(0.01708)	(0.12433)

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.2.4 Selected model for TKN removal of NBS A

Model (1) was chosen to simulate the TKN removal of NBS A, since it was the one with best statistical performance in terms of R2 adjusted. The expert-based evaluation was also positive, as all key variables are consistent with the TN removal model.

Table 5. Detailed results of multiple linear regression for NBS A for TKN. Heteroskedastic robust standard errors in parentheses. The selected statistical model is highlighted in red.

NBS A – TKN – Linear Models	(1)	(2)	(3)	(4)
Goodness of fit indexes				
Observations	14	14	14	14
R2	0.578	0.582	0.578	0.582
R2 adjusted	0.39	0.321	0.39	0.321
DoF model	4	5	4	5
DoF residuals	9	8	9	8
RMSE	0.16	0.169	0.16	0.169
Obs./Parameters	2.33	2.00	2.33	2.00
Max residual (positive)	0.228	0.221	0.228	0.221
Max residual (negative)	-0.223	-0.233	-0.223	-0.233
SD residuals	0.133	0.132	0.133	0.132
Selected parameters				
Specific water inflow	-0.00010***	-0.00003	-0.00010***	-0.00003
	(0.00002)	(0.00015)	(0.00002)	(0.00015)
ww_mix_RNF	-0.22470***	-0.22323***	-0.22470***	-0.22323***
	(0.06352)	(0.06375)	(0.06352)	(0.06375)
Previous treatment Primary NBS	-0.19523**	-0.18736*	-0.19523**	-0.18736*
	(0.07405)	(0.09395)	(0.07405)	(0.09395)
Previous treatment Primary NBS + Secondary NBS	-0.34926***	-0.35311***	-0.34926***	-0.35311***
	(0.07391)	(0.07749)	(0.07391)	(0.07749)
TKN loading rate		-0.00099		-0.00099
		(0.00215)		(0.00215)

NBS A – TKN – Linear Models	(1)	(2)	(3)	(4)
Constant	0.74648***	0.74865***	0.74648***	0.74865***
	(0.01256)	(0.01400)	(0.01256)	(0.01400)

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.2.5 Selected model for BOD5 removal of NBS A

All the models perform in a similar manner for BOD_5 removal in terms of statistical performance. **Model (1)** was chosen due to a slightly higher R2 adjusted. The expert-based evaluation was also positive, since all key variables are consistent with literature on constructed wetlands (see Kadlec and Wallace, 2009). In particular, it can be noted that:

— the negative effect – i.e. lower BOD_5 removal % – of a higher specific water inflow is in line with the shorter hydraulic retention time of the system, in analogy with TN removal;

— BOD_5 removal results positively affected – i.e. higher BOD_5 removal % – in case of manure-driven wastewater mixed with agricultural runoff, contrarily to TN removal; this can also be considered reliable, because, from the point of view of BOD_5 removal, dilution with less strong wastewater (agricultural runoff) can help in decreasing influent BOD_5 concentrations (extremely high in manure-driven wastewater), contributing to operate the system in most appropriate way;

— despite being counterintuitive, even the negative effect – i.e. lower BOD_5 removal % – of a higher average annual temperature does not disagree with recent literature; BOD_5 is mainly removed with biological processes in wetlands, and a positive effect with temperature should be expected, as pictured by older CW design models (Reed et al., 1995); however, recent works have questioned this dependency, reporting fitting models with a negative effect of temperature (Kadlec and Wallace, 2009; Nivala et al., 2019), as happened to our statistical fitting; this counterintuitive result is not yet clearly understood in literature (Nivala et al., 2019) and, therefore, cannot be a reason to discard the model.

Table 6. Detailed results of multiple linear regression for NBS A for BOD_5. Heteroskedastic robust standard errors in parentheses. The selected statistical model is highlighted in red.

NBS A – BOD_5 – Linear models	(1)	(2)	(3)	(4)
Goodness of fit indexes				
Observations	21	21	21	21
R2	0.809	0.816	0.809	0.816
R2 adjusted	0.776	0.77	0.776	0.77
DoF model	3	4	3	4
DoF residuals	17	16	17	16
RMSE	0.120	0.121	0.120	0.121
Obs./Parameters	4.20	3.50	4.20	3.50
Max residual (positive)	0.216	0.211	0.216	0.211
Max residual (negative)	-0.235	-0.225	-0.235	-0.225
SD residuals	0.110	0.108	0.110	0.108
Selected parameters				
Average annual Temperature	-0.04177***	-0.04364***	-0.04177***	-0.04364***
	(0.00698)	(0.00726)	(0.00698)	(0.00726)
Specific water inflow	-0.00027***	-0.00024***	-0.00027***	-0.00024***

NBS A – BOD_5 – Linear models	(1)	(2)	(3)	(4)
	(0.00003)	(0.00004)	(0.00003)	(0.00004)
ww_mix_RNF	0.16764***	0.16018**	0.16764***	0.16018**
	(0.05775)	(0.05888)	(0.05775)	(0.05888)
BOD5 loading rate		-0.00050		-0.00050
		(0.00053)		(0.00053)
Constant	1.16629***	1.20373***	1.16629***	1.20373***
	(0.06661)	(0.07763)	(0.06661)	(0.07763)

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.2.6 Selected model for COD removal of NBS A

All models perform in a similar manner for COD removal in terms of statistical performance. **Model (1)** was chosen due to a slightly higher R2 adjusted. The expert-based evaluation was also positive, since all the key variables are consistent with literature on constructed wetlands (see Kadlec and Wallace, 2009). In particular, it can be noted that:

— the negative effect – i.e. lower COD removal % – of a higher specific water inflow is in line with the shorter hydraulic retention time of the system, in analogy with TN and BOD5 removal;

— the negative effect – i.e. lower COD removal % – in case of a primary treatment with NBS is also consistent, indicating a better performance of technological primary treatment (grey solution) instead of NBS (anaerobic pond) primary treatment;

Table 7. Detailed results of multiple linear regression for NBS A for COD. Heteroskedastic robust standard errors in parentheses. The selected statistical model is highlighted in red.

NBS A – COD – Linear models	(1)	(2)	(3)	(4)
Goodness of fit indexes				
Observations	19	19	19	19
R2	0.544	0.561	0.544	0.561
R2 adjusted	0.487	0.473	0.487	0.473
DoF model	2	3	2	3
DoF residuals	16	15	16	15
RMSE	0.183	0.186	0.183	0.186
Obs./Parameters	4.75	3.80	4.75	3.80
Max residual (positive)	0.311	0.329	0.311	0.329
Max residual (negative)	-0.495	-0.453	-0.495	-0.453
SD residuals	0.173	0.170	0.173	0.170
Selected parameters				
Specific water inflow	-0.00028***	-0.00031***	-0.00028***	-0.00031***
	(0.00005)	(0.00006)	(0.00005)	(0.00006)
Previous treatment Primary NBS	-0.21592**	-0.19259*	-0.21592**	-0.19259*
	(0.08372)	(0.10473)	(0.08372)	(0.10473)
COD loading rate		0.00037		0.00037
		(0.00052)		(0.00052)
Constant	0.85499***	0.80862***	0.85499***	0.80862***
	(0.06490)	(0.12097)	(0.06490)	(0.12097)

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.2.7 Selected model for TSS removal of NBS A

Despite the better statistical fitting of model (4), **Model (2)** was chosen since the negative effect of average depth provided by model (4) was not convinging fot the experts (lower depths would mean lower hydraulic retention times and, therefore, lower TSS removal). The expert-based evaluation of Model (2) was also positive, as all key variables are consistent with previous removal models.

Table 8. Detailed results of multiple linear regression for NBS A for TSS. Heteroskedastic robust standard errors in parentheses. The selected statistical model is highlighted in red.

NBS A – TSS – Linear models	(1)	(2)	(3)	(4)
Goodness of fit indexes				
Observations	35	22	35	22
R2	0.320	0.631	0.511	0.776
R2 adjusted	0.254	0.544	0.427	0.687
DoF model	2	3	4	5
DoF residuals	31	17	29	15
RMSE	0.193	0.165	0.17	0.137
Obs./Parameters	8.75	4.40	5.83	3.14
Max residual (positive)	0.331	0.233	0.319	0.139
Max residual (negative)	-0.504	-0.401	-0.311	-0.206
SD residuals	0.185	0.148	0.157	0.116
Selected parameters				
ww_mix_RNF	-0.12901**	-0.07168	-0.13500**	-0.11976
	(0.05803)	(0.08326)	(0.05912)	(0.11656)
Previous treatment Primary grey	0.27921***	0.39646***	0.27121***	0.37745***
	(0.05709)	(0.06168)	(0.05629)	(0.05322)
Filling media Porous media + soil	0.26096***	0.36227***	0.25722***	0.34704***
	(0.04547)	(0.06103)	(0.04209)	(0.05058)
Area			0.00587***	0.18006
			(0.00096)	(0.29106)
Average depth			-0.01736***	-0.01388***
			(0.00149)	(0.00181)
Solid loading rate		-0.00038		-0.00088
		(0.00081)		(0.00092)
Constant	0.63904***	0.54407***	0.65625***	0.57233***
	(0.04547)	(0.06855)	(0.04327)	(0.06027)

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.3 Model selection for NBS B, VDDs and wetlands for diffuse pollution

The detailed analysis of MCorA for NBS is reported in Annex 8. The multiple linear regression analysis was performed by regressing the abatement efficiency (for each one of the 4 contaminants, i.e., Nitrogen N, Nitrate N_NO3, total Phosphorous P and Phosphates P_PO4) on the candidate "causal factors" including the characteristics of the wetland NBS (**Table 9**).

The results of the analysis are reported in the following sub-sections.

Table 9. List of variables for multiple linear regression analysis of NBS B, VDDs and wetlands dataset

Variable name	Variable description
Dependent variables	
NNo3_abat	Removal N-NO3
TN_abat	Removal N
TP_abat	Removal P
PO4_abat	Removal PO4
Predictors Model (1) and (2) – MCorA selected variables	
C_avT	Average annual Temperature
C_n_cold	Average annual n of days with T < threshold C
C_StdDev	Temporal uniformity of precipitation pattern (standard deviation)
C_p	Average annual precipitation - 2
C_GAI	Global aridity index (adj)
C_PET	Potential annual evapo-transpiration (Global AI-PET)
D_T1_VDD	Type VDD
D_T1_FWS_in	Type FWS inline
D_T1_FWS_off	Type FWS offline
D_T1_hybrid	Type Hybrid
D_T2_VDD	Type VDD
D_T2_wetland	Type wetland
D_Area	Area
D_NNo3	N-NO3 loading rate
D_TN	TN loading rate
D_TP	Total Phosporous loading rate
D_TSS	Solid loading rate
Additional predictors for Model (3) and (4) – All variables	
L_ALTITUDE	Altitude
D_Depth	Average depth
D_Ratio	Aspect-Ratio
D_veg_emergent	Type of aquatic vegetation Emergent
D_veg_othr	Type of aquatic other combination
D_sub	Substrate

2.1.1.3.1 General consideration on the results of multiple linear regression analysis *for NBS B, VDDs and wetlands*

The results of the multiple regression analysis for NBS B, VDDs and wetlands, are shown in the following sub-sections. The results indicate the presence of substantial heterogeneity between contaminants. Specifically, the variables that significantly explain the abatement efficiency (and hence included in the models) vary depending on the contaminant. In addition, when they occur in different groups of models, they sometimes change sign (e.g. the Area is positively associated with efficiency for N_NO3, but negatively for PO4).

On the contrary, within the group of models explaining the abatement efficiency of a given compound, the coefficients show in general a good consistency (i.e. they do not change sign). In the few cases in which the coefficient changes sign, it also loses statistical significance.

The variables associated with the abatement efficiency of more than one contaminant are:

- *Area*: it appears in 2 out of 4 cases (PO4 and NO3), negative and significant for the former and positive and significant for the latter;
- *Global aridity index*: appears three times (NO3, N and P) and, when significant, is negatively associated with the abatement efficiency;
- *Potential annual evapotranspiration*: appears twice (N and P) and generally results negative and significant;
- *Aspect ratio*: appears three times, but only in two cases is significant; the association is positive for PO4 and P, while is negative for NO3.

When taken into account, the contaminant loading rates turn out to be significantly associated with the abatement efficiency. No clear pattern, however, emerges from this analysis. In fact, the loading rates of Phosphates (PO4) and Nitrogen (N) are positively associated with the abatement efficiency, whereas those of Nitrate (NO3) and Phosphorous (P) are negatively associated with abatement efficiency. In two cases, that is for N and P, the Solid loading rate was also considered, which resulted to be positively and significantly associated with the abatement efficiency of the latter (i.e., P). More importantly, it should be noted that in general (three out of four cases) the inclusion of the load (loading rate) comes at the price of a significant reduction in the sample size, while increasing the number of parameters to be estimated. The very small sample poses hence a serious threat to the robustness of these models. Therefore, the models that do consider the loading rates should not be adopted as working tools.

Incidentally, some of the variables discarded by the MCorA turned out to be significant only for total Phosphorous (P) and Nitrates (NO3).

Finally, the selection of climate variables related to precipitation can be considered a safe result, since it is well-known that the performance of wetlands in the removal of diffuse pollution is strongly influenced by stochastic precipitation patterns (Kadlec and Wallace, 2009; Ioannidou and Stefanakis, 2020).

2.1.1.3.2 Selected model for TN removal of NBS B, VDDs and wetlands for diffuse pollution control

Although worse than (2) and (4), model (1) is much more robust as Obs/Par is much higher, and a value of 1.8-1.6 of model (3) and (4) respectively is too low to be acceptable; in addition, model (4) shows an unrealistic parameter value for the Global aridity index. When compared to (3), model (1) performs slightly worse, but is again significantly more robust and substantially equivalent in other respects. From the point of view of expert judgment, the dependencies on the selected variable are in accordance with literature on constructed wetlands (see Kadlec and Wallace, 2009). In particular, it can be noted that:

- the positive effect – i.e. higher TN removal % – with higher precipitation is significant, since it means that a greater load is treated by the wetland system;
- the negative effect – i.e. lower TN removal % – with higher global aridity index and higher evapotranspiration is also consistent, since greater water losses by evapotranspiration lead to higher effluent concentrations (due to water budget) and, therefore, lower removal performance in % between in and out.

Therefore, **Model (1)** was selected to estimate TN removal of VDDs and wetlands for agricultural diffuse pollution control.

Table 10. Detailed results of multiple linear regression for NBS B, VDDs and wetlands, for TN. Heteroskedastic robust standard errors in parentheses. The selected statistical model is highlighted in red.

NBS B, VDD and wet – TN Linear Models	**(1)**	**(2)**	**(3)**	**(4)**
Goodness of fit indexes				
Observations	73	11	73	11
R2	0.26467	0.65901	0.27766	0.79190
R2 adjusted	0.233	0.318	0.235	0.480
DoF model	3	5	4	6
DoF residuals	69	5	68	4
RMSE	0.261	0.323	0.261	0.282
Obs./Parameters	18.3	1.8	14.6	1.6
Max residual (positive)	0.4993604	0.3979851	0.5142468	0.2772857
Max residual (negative)	-0.6366287	-0.2733054	-0.62463	-0.2242072
SD residuals	0.2555567	0.2280622	0.2532902	0.1781636
Selected parameters				
Average annual precipitation	0.00087***	0.00308	0.00084***	-0.03458
	(0.00023)	(0.00388)	(0.00023)	(0.02572)
Global aridity index (adj)	-1.12099***	-4.29819	-1.07039***	55.24712
	(0.24083)	(6.14445)	(0.23932)	(40.48311)
Potential annual evapo-transpiration	-0.00039**	-0.00093	-0.00037*	0.00854
	(0.00019)	(0.00222)	(0.00019)	(0.00614)
TN loading rate		0.08334**		0.03987
		(0.02069)		(0.04049)
Solid loading rate		-0.00441		-0.00230
		(0.00235)		(0.00273)
L_ALTITUDE			0.00015*	-0.03330
			(0.00007)	(0.02402)
Constant	0.98180***	2.00350	0.92384***	-12.79791
	(0.21958)	(3.53662)	(0.22127)	(9.39286)

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.3.3 Selected model for N-NO3 removal of NBS B, VDDs and wetlands for diffuse pollution control

The inclusion of the loading rates (model 2 and 4) does not lead to a drastic reduction in the sample size, and models (2) and (4) still present an acceptable level of Obs./Par. In addition, they perform substantially better than models (1) and (3). Model (2) performs very similarly to model (4), but the former has a slightly more symmetrical distribution of residuals (model 4 has a max positive residual too high compared to the min) and was chosen from a point of view of statistical goodness. Moreover, the parameters selected by Model (2) also agree with expert-based judgment and known literature (Kadlec and Wallace, 2009), in particular:

— the negative effect – i.e. lower N-NO3 removal % – with a higher number of months at low temperature is consistent, since it is well-known that nitrogen removal in CWs is principally driven by bacteria families sensitive to temperature variation (Kadlec and Wallace, 2009; Vymazal 2007);

— a negative effect – i.e. lower N-NO3 removal % – is also expected with a less uniform monthly precipitation pattern, since it can be correlated to a less uniform water flow entering the wetland and, moreover, less uniform hydraulic retention times, worsening the treatment performance;

- the negative effect – i.e. lower N-NO3 removal % – with a higher nitrate loading rate can also be explained from a biological perspective, indeed, a higher nitrate load could encounter a carbon deficit for denitrification (Kadlec and Wallace, 2009); since the source of C in agricultural runoff is usually low and rather diluted, C deficit can hinder denitrification rates;
- the negative effect – i.e. lower N-NO3 removal % – with a higher global aridity index is also reasonable for the same considerations made for TN removal;
- the positive effect – i.e. higher N-NO3 removal % – if the NBS is a VDD instead of a FWS is less justified by literature, which shows comparable removal efficiencies (e.g. Vymazal and Březinová, 2018). Analysing in detail the dataset used for model fitting, it's clear that the difference between VDDs and FWS is affected by a lower number of samples of VDDs and is mainly driven by the single case of Robertson and Merkley (2009), in which, probably, the use of a particular substrate (woodchips – carbon source for denitrification) boosted the nitrate removal. Since the use of a particular substrate is not the common design approach of a VDD, it is suggested to not consider, in terms of favourability and opportunity maps, a greater performance of VDDs in comparison to FWS.

Therefore, **Model (2)** was selected to estimate N-NO3 removal of VDD and wetlands for agricultural diffuse pollution control.

Table 11. Detailed results of multiple linear regression for NBS B, VDDs and wetlands, for N-NO3. Heteroskedastic robust standard errors in parentheses. The selected statistical model is highlighted in red.

NBS B, VDD and wet – N-NO3 Linear Models	**(1)**	**(2)**	**(3)**	**(4)**
Goodness of fit indexes				
Observations	53	42	53	42
R2	0.32781	0.67481	0.32781	0.69095
R2 adjusted	0.287	0.630	0.287	0.638
DoF model	3	5	3	6
DoF residuals	49	36	49	35
RMSE	0.290	0.168	0.290	0.167
Obs./Parameters	13.3	7.0	13.3	6.0
Max residual (positive)	0.698	0.252	0.698	0.866
Max residual (negative)	-0.826	-0.522	-0.826	-0.114
SD residuals	0.282	0.158	0.282	0.230
Selected parameters				
Average annual n of days with T < threshold C		-0.04549***		-0.04299***
		(0.00884)		(0.00885)
Temporal uniformity of precipitation pattern		-0.09511*		-0.08345*
		(0.04740)		(0.04798)
N-NO3 loading rate		-0.00924*		-0.01009*
		(0.00476)		(0.00538)
Global aridity index (adj)		-0.53846***		-0.51608***
		(0.07754)		(0.07654)
Type VDD		0.16621***		0.32664***
		(0.05892)		(0.08452)
Type FWS offline	0.38916***		0.38916***	
	(0.11643)		(0.11643)	
Type wetland	-0.39082***		-0.39082***	
	(0.13427)		(0.13427)	

NBS B, VDD and wet – N-NO3 Linear Models	(1)	(2)	(3)	(4)
Area	0.00230***		0.00230***	
	(0.00077)		(0.00077)	
Aspect-Ratio				-0.00274***
				(0.00097)
Constant	0.49667***	1.27037***	0.49667***	1.24664***
	(0.08573)	(0.11947)	(0.08573)	(0.11694)

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.3.4 Selected model for TP removal of NBS B, VDDs and wetlands for diffuse pollution control

While models (2) and (4) perform better in terms of R2, they rely on an insufficient number of observations (Obs/Par =2.5) compared to model (3) and hence lose robustness. Moreover, model (3) selected variables that are strongly in line with evidence from literature (Kadlec and Wallace, 2009; Vymazal 2007), in particular:

— the negative effect – i.e. lower TP removal % – with a higher global aridity index is also reasonable for the same considerations made for TN removal;

— the positive effect – i.e. higher TP removal % – with a higher aspect-ratio is also reasonable, as it means running wetlands and VDDs more proximal to a plug-flow reactor, minimizing preferential paths;

— the positive effect – i.e. higher TP removal % – due to the presence of plants and additional substrates is also in line with the general understanding of P removal processes in wetlands, mainly driven by sorption by either plant uptake or adsorption on substrate (Kadlec and Wallace, 2009; Vymazal 2007).

Therefore, **Model (3)** was selected to estimate TP removal of VDDs and wetlands for agricultural diffuse pollution control.

Table 12. Detailed results of multiple linear regression for NBS B, VDD and wetland, for TP. Heteroskedastic robust standard errors in parentheses. The selected statistical model is highlighted in red.

NBS B, VDD and wet – TP Linear Models	(1)	(2)	(3)	(4)
Goodness of fit indexes				
Observations	43	10	39	10
R2	0.18982	0.87161	0.44579	0.87161
R2 adjusted	0.149	0.807	0.381	0.807
DoF model	2	3	3	3
DoF residuals	40	6	34	6
RMSE	0.387	0.112	0.339	0.112
Obs./Parameters	14.3	2.5	9.8	2.5
Max residual (positive)	0.6180459	0.142515	0.5688084	0.142515
Max residual (negative)	-1.143945	-0.1121448	-1.057382	-0.1121448
SD residuals	0.3772496	0.0914246	0.3210826	0.0914246
Selected parameters				
Potential annual evapo-transpiration	-0.00049***	-0.00101***	-0.00029**	-0.00101***
	(0.00012)	(0.00018)	(0.00011)	(0.00018)
Total Phosporous loading rate		-1.01769***		-1.01769***
		(0.18456)		(0.18456)

NBS B, VDD and wet – TP Linear Models	(1)	(2)	(3)	(4)
Solid loading rate		0.00367**		0.00367**
		(0.00100)		(0.00100)
Global aridity index (adj)	-0.45024***			
	(0.16620)			
Aspect-Ratio			0.00186***	
			(0.00045)	
Type of aquatic vegetation Emergent			0.72074***	
			(0.22097)	
Substrate			0.47749***	
			(0.06066)	
Constant	1.25588***	1.77881***	-0.08845	1.77881***
	(0.22674)	(0.21368)	(0.23514)	(0.21368)

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.3.5 Selected model for P-PO4 removal of NBS B, VDDs and wetlands for diffuse pollution control

Although slightly worse than (3) in terms of adjusted R2, model (1) is more robust because it has more DoF residuals and a higher observations/parameters ratio, while it is practically equivalent in other respects. On the other hand, the expert judgment was not positive, since the negative dependence on the area is not in agreement with literature evidence. This could probably be due to the smaller number of samples in the dataset (maximum 17), in comparison to the TP dataset (maximum 43). Therefore, **none** of the statistical model was selected and it is suggested that P-PO4 removal is not predicted by cause-effect models.

If the VDDs and wetlands are placed in optimal functioning conditions and with dimensions in line with literature range of design variables, the median removal performance (50^{th} percentile) can be assumed for the pollutant P-PO4.

Table 13. Detailed results of multiple linear regression for NBS B, VDDs and wetlands, for P-PO4. Heteroskedastic robust standard errors in parentheses. None of the statistical model is selected.

NBS B, VDD and wet – P-PO4 Linear Models	(1)	(2)	(3)	(4)
Goodness of fit indexes				
Observations	17	13	17	13
R2	0.52373	0.51022	0.57607	0.51022
R2 adjusted	0.456	0.412	0.478	0.412
DoF model	2	2	3	2
DoF residuals	14	10	13	10
RMSE	0.280	0.268	0.274	0.268
Obs./Parameters	5.7	4.3	4.3	4.3
Max residual (positive)	0.404	0.441	0.368	0.441
Max residual (negative)	-0.725	-0.518	-0.693	-0.518
SD residuals	0.262	0.245	0.247	0.245
Selected parameters				
Average annual Temperature	0.03849*		0.04097*	
	(0.02147)		(0.02086)	
Area	-0.00452***	-0.00465***	-0.00431***	-0.00465***
	(0.00107)	(0.00066)	(0.00108)	(0.00066)

Total Phosphorous loading rate		0.62783**		0.62783**
		(0.26808)		(0.26808)
Aspect-Ratio			0.00692	
			(0.00404)	
Constant	-0.04588	0.29919**	-0.15115	0.29919**
	(0.21984)	(0.10479)	(0.22379)	(0.10479)

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.4 Model selection for NBS B, buffer strips

The detailed analysis of MCorA for NBS is reported in Annex 8. The multiple linear regression analysis was performed by regressing the abatement efficiency on the candidate "causal factors" including the characteristics of the NBS Buffer strips. In this case, however, the analysis was run on two different subsamples: buffer strips aimed at intercepting the surface diffuse pollution driven by runoff (BS-R) and buffer strips aimed at intercepting subsurface diffuse pollution driven by groundwater (BS-G).

Table 14. List of variables for multiple linear regression analysis of NBS B, buffer strip dataset

Variable name	Variable description
Predictors Model (1) and (2) – MCorA selected variables	
L_ALTITUDE	Altitude
L_WATER	water table excursion
L_MEAN_WATER	Mean Water table depth
L_TS_clay	Type of soil CLAY
L_TS_loam	Type of soil LOAM
L_TS_sand	Type of soil SAND
L_TS_silt	Type of soil SILT
C_n_cold	Average annual n of months with T < threshold C
C_PET	Potential annual evapo-transpiration (Global AI-PET)
D_TBS_R	Type BS-R
D_TBS_G	Type BS-G
Additional predictors for Model (3) and (4) – All variables	
L_SURFACE	Surface slope
c_avT	Average annual Temperature
C_Stdev	Temporal uniformity of precipitation pattern (standard deviation)
C_p	Average annual precipitation - 2
C_AridIx	Global aridity index
D_TOPOGRAPHIC	Topographic adjustment
D_WIDTH	Width
D_Tv_herb	Type Herbaceous
D_Tv_trees	Type Trees
D_Tv_shrubs	Type Shrubs
Load variables	
D_TN	Input conc. TN
D_NO3	Input conc. NO3
D_TP	Input conc. TP
D_PO4	Input conc. PO4
D_TSS	Input conc. TSS

Variable name	Variable description
D_SED	Input conc. Sed

2.1.1.4.1 General considerations on the results of multiple linear regression analysis *for NBS B, buffer strips for surface runoff interception (BS-R)*

The empirical analysis indicates moderate between-contaminants heterogeneity. In particular, the model specifications (i.e., the variables that are found to be significantly associated with the abatement efficiency) change moderately across the contaminants. For example, among the variables identified as relevant by the MCorA, *Altitude* explains the abatement efficiency of three out of six contaminants, exhibiting a negative correlation with NO3 and SED abatement efficiency, and mixed in the case of TN abatement.

On the other hand, within the group of models explaining the abatement efficiency of the same contaminant, the coefficients show a moderate level of consistency. Indeed, in five cases the coefficients switch sign, in two cases loosing statistical significance.

The variables associated with the abatement efficiency that appear more frequently in model specifications are:

— *Width*, which is always positively and significantly associated with the abatement efficiency of NO3, P, PO4 and SED.

— *Altitude*, which appears in 4 out of 6 cases (NO3, SED, TN, TSS). The estimated coefficients tend to be negative;

— *Global aridity index*, which is negatively and significantly correlated with the abatement efficiency of SED and TSS and positively and significantly correlated with the abatement efficiency of NO3 and P.

No clear pattern emerges with the inclusion of the loading rates of the contaminants, an exercise which often comes at the cost of a significant reduction in sample size. In two cases, the relationship is positive and significant; in other cases, however, the coefficients are positive (but not significant). On the other hand, the loading rates of other contaminants (e.g., the loading rate of TN in the regression for the abatement of NO3) tend to be negatively associated with the abatement efficiency. This seems to say that a higher level of aggregate contamination (i.e., the presence of other contaminants) reduces the abatement efficiency of each specific contaminant.

The results of the multiple regression analysis are reported in the following sub-sections.

Despite a good extension of the dataset, robust indications on BS-R performance did not clearly emerge from linear regression analyses. This is in line with the current high uncertainty on BS-R removal performance and removal mechanisms reported in literature. It is in fact known that BS-Rs target to intercept pollutant conveyed by stormwater runoff, and principally those linked to sediment trapping, i.e. TN and TP. However, there are still uncertainties about removal efficiencies (Vidon et al. 2019; Stutter et al., 2019). Indeed, also previous meta-analytic analyses often show low fitting performance (e.g. Mayer et al., 2007). In terms of BS-Rs, Zhang et al. (2010) reports good fitting performance from a meta-analysis, identifying vegetation, slope, and width as key variables for BS-Rs. If the removal mechanisms were related to sediment trapping, the same variable would be expected in the linear model for Sediment, TP, and TN. This did not occur, raising doubts about the confidence of the proposed model. This can be partly explained by the fact that often, monitored buffer strips in peer review literature are already in optimal functioning conditions. For BS-Rs, this is the case for the slope variable: the optimal value suggested by Zhang et. (2010) is less than 10% and the 3rd quartile of NBS BS-R dataset is 8.5%, meaning that the samples were probably not sufficient to capture the detrimental effect of too high slopes with linear regression. Due to all these uncertainties, it was preferred to give more importance to expert judgment, which gave positive feedback for the TP model and negative for other models. Therefore, it is suggested to use only the TP model for the favourability and opportunity maps, assuming the median removal performance (50th percentile) for other pollutants. For completeness, the fitted model for each pollutant is discussed from a statistical perspective below, providing a detailed expert-based justification for the selected model only.

2.1.1.4.2 Selected model for TP removal of NBS, buffer strips for runoff interception

Model (2) performs slightly better than (1) in virtually all the statistics. The inclusion of loading rates (models 3, 4) marginally increases the fit but reduces the number of observations to 24, which lowers the observations/parameters ratio too much. This is also the only fitting with selected parameters in line with experts' expectations according to literature evidence (Vidon et al., 2019), in particular:

- the positive effect – i.e. higher TP removal % – when clay[8] is present is consistent with a higher P sorption capacity of clay particles;
- the positive effect – i.e. higher TP removal % – with higher temperatures and drier conditions (higher global aridity indexes) can be justified by less humid conditions, which favour a higher infiltration capacity of the soil and, therefore, greater infiltration of intercepted runoff (Vidon et al., 2019);
- the negative effect – i.e. lower TP removal % – with higher annual precipitation can be explained by a higher annual load to be intercepted, decreasing the buffer strip capacity to intercept the annual load;
- the positive effect – i.e. higher TP removal % – with a larger width is also in line with literature evidence (larger contact surface for TP interception) and in line with several literature studies (e.g. Zhang et al., 2010);
- the positive effect – i.e. higher TP removal % – in presence of herbaceous vegetation is also in line with the recent literature review (Vidon et al., 2019) since the higher density of shrubs helps to slow down the runoff, favouring infiltration and limiting preferential paths that can occur if only trees are planted.

Therefore, **Model (2)** was selected to estimate TP removal of buffer strips for interception of surface runoff.

Table 15. Detailed results of multiple linear regression for NBS B, BS-Rs (buffer strips for surface runoff interception), for TP. Heteroskedastic robust standard errors in parentheses. None of the statistical model is selected.

NBS B, BS-R – TP **Linear Models**	**(1)**	**(2)**	**(3)**	**(4)**
Goodness of fit indexes				
Observations	37	37	24	24
R-squared	0.10706	0.6371	0.58547	0.83918
R2 adjusted	0.0816	0.565	0.523	0.769
DoF model	1	5	3	7
DoF residuals	35	30	20	16
RMSE	0.182	0.125	0.116	0.0807
Obs./Parameters	18.5	6.2	6.0	3.0
SD residuals	0.1796718	0.1145418	0.1079997	0.0672688

[8] It must be clarified that "type of soil CLAY" is a binary proxy to identify the presence of clay, based on the USDA classification. The proxy value is assumed to be equal to 1 if clay is within the soil texture classification (i.e. CLAY, SANDY CLAY, SANDY CLAY LOAM, CLAY LOAM, SILTY CLAY, SILTY CLAY LOAM) and equal to 0 if not (i.e. SAND, LOAMY SAND, SANDY LOAM, LOAM, SILT LOAM, SILT)

NBS B, BS-R – TP Linear Models	**(1)**	**(2)**	**(3)**	**(4)**
Max residual (negative)	-0.4349062	-0.2730779	-0.2070933	-0.1511715
Max residual (positive)	0.282789	0.1971332	0.1835526	0.1145917
Selected parameters				
Type of soil CLAY	0.14907***	0.16350**	0.03206	0.15729*
	(0.04893)	(0.06405)	(0.08806)	(0.07492)
Average annual Temperature		0.04093***		0.03115
		(0.01383)		(0.02109)
Average annual precipitation		-0.00161***		-0.00139**
		(0.00030)		(0.00063)
Global aridity index		1.15638***		1.05362**
		(0.28515)		(0.47365)
Width		0.02620***		0.02037***
		(0.00477)		(0.00427)
Type Herbaceous		0.77568***		
		(0.18110)		
Input conc. TP			-0.00979	0.00392
			(0.00841)	(0.00730)
Input conc. TSS			0.00000	-0.00001
			(0.00001)	(0.00001)
Constant	0.68824***	-0.18858	0.84166***	0.72454***
	(0.03720)	(0.30222)	(0.03503)	(0.15875)

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.4.3 Selected model for P-PO4 removal of NBS, buffer strips for runoff interception

All the variables included in model 2 are statistically significant and the adjusted R2 is almost 0.6. The inclusion of loading rates (models 3, 4) reduces the sample size to 14, therefore undermining the robustness of the analysis. However, the negative effect of cold months seems too strong and difficult to understand from a physico-chemical perspective (the solubility of dissolved P increases with temperature, so lower temperatures should have a positive effect). Since dissolved P is not commonly targeted by BS-Rs (Vidon et al., 2019), it is suggested not to use any of the proposed linear models for the favourability and opportunities maps. If the BS-R is placed in optimal functioning conditions and with dimensions in line with the literature range of design variables, the median removal performance (50th percentile) can be assumed.

Table 16. Detailed results of multiple linear regression for NBS B, BS-R (buffer strip for surface runoff interception), for P-PO4. Heteroskedastic robust standard errors in parentheses. The selected statistical model is highlighted in red.

NBS B, BS-R – P-PO4 Linear Models	**(1)**	**(2)**	**(3)**	**(4)**
Goodness of fit indexes				
Observations	36	36	14	14
R-squared	0.47694	0.61218	0.72204	0.86999
R2 adjusted	0.462	0.589	0.639	0.812
DoF model	1	2	3	4
DoF residuals	34	33	10	9
RMSE	0.342	0.299	0.342	0.247
Obs./Parameters	18.0	12.0	3.5	2.8

NBS B, BS-R – P-PO4 Linear Models	(1)	(2)	(3)	(4)
SD residuals	0.3374049	0.2905312	0.3003893	0.2054392
Max residual (negative)	-0.9536143	-0.7705883	-0.5628482	-0.3738503
Max residual (positive)	0.536486	0.4179276	0.6335474	0.3226813
Selected parameters				
Average annual n of months with T < threshold C	-0.41622***	-0.44767***	-0.35266***	-0.30792***
	(0.09840)	(0.08931)	(0.09517)	(0.06261)
Input conc. TP			0.03581	0.05561
			(0.05863)	(0.03714)
Input conc. TN			-0.02279	-0.02707*
			(0.02218)	(0.01346)
Width		0.03126***		0.04464***
		(0.00891)		(0.01333)
Constant	2.86714***	2.76049***	2.82857***	2.04450***
	(0.51049)	(0.44383)	(0.55075)	(0.34580)

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.4.4 Selected model for TN removal of NBS, buffer strips for runoff interception

Model 3 exhibits the highest R2 adjusted and the highest accuracy (lowest RMSE and SD residuals) and a low, but perhaps still acceptable observations/parameters ratio. The sample size of models (1) and (2) is much higher, but the goodness of fit of the model is much lower. None of the models was selected due to low R2 and inconsistent selected variables in comparison to TP model. Therefore, it is suggested not to use any of the proposed linear models for the favourability and opportunities maps. If the BS-R is placed in optimal functioning conditions and with dimensions in line with the literature range of design variables, the median removal performance (50th percentile) can be assumed.

Table 17. Detailed results of multiple linear regression for NBS B, BS-R (buffer strip for surface runoff interception), for TN. Heteroskedastic robust standard errors in parentheses. None of the statistical model is selected.

NBS B, BS-R – TN Linear Models	(1)	(2)	(3)	(4)
Goodness of fit indexes				
Observations	51	51	26	26
R-squared	0.06598	0.10405	0.3605	0.36819
R2 adjusted	0.0469	0.0667	0.273	0.248
DoF model	1	2	3	4
DoF residuals	49	48	22	21
RMSE	0.206	0.204	0.166	0.168
Obs./Parameters	25.5	17.0	6.5	5.2
SD residuals	0.2038515	0.1996539	0.1553202	0.1543825
Max residual (negative)	-0.5264432	-0.5049539	-0.422344	-0.4084539
Max residual (positive)	0.2977648	0.3086385	0.2097712	0.2094635
Selected parameters				
Altitude	0.00029*	0.00033**	-0.00001	0.00003
	(0.00016)	(0.00016)	(0.00017)	(0.00021)
Input conc. TN			0.00158	0.00171
			(0.00184)	(0.00193)
Input conc. TSS			-0.00001**	-0.00001*
			(0.00001)	(0.00001)
Type Shrubs		0.21395**		0.07261
		(0.08082)		(0.13866)

NBS B, BS-R – TN Linear Models	(1)	(2)	(3)	(4)
Constant	0.58988*** (0.06683)	0.56788*** (0.07003)	0.78976*** (0.09567)	0.75782*** (0.12951)

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.4.5 Selected model for N-NO3 removal of NBS, buffer strips for runoff interception

The inclusion of Loading rates and additional variables increases the goodness of fit and the accuracy, and Model 4 turns out to be the one that performs best, but at the expense of a reduced sample. Therefore, considering the robustness of the model, Model 3 could be chosen. However, expert-based evaluation found the selected variables to be inconsistent; particularly, the soil type variable changes the sign from one model to another, rising doubts about consistency. Since nitrates is not commonly targeted by BS-Rs (Vidon et al., 2019), it is suggested not to use any of the proposed linear models for the favourability and opportunities maps. If the BS-R is placed in optimal functioning conditions and with dimensions in line with the literature range of design variables, the median removal performance (50^{th} percentile) can be assumed.

Table 18. Detailed results of multiple linear regression for NBS B, BS-Rs (buffer strip for surface runoff interception), for N-NO3. Heteroskedastic robust standard errors in parentheses. None of the statistical model is selected.

NBS B, BS-R – N-NO3 Linear Models	(1)	(2)	(3)	(4)
Goodness of fit indexes				
Observations	45	45	31	31
R-squared	0.32588	0.44653	0.63369	0.74413
R2 adjusted	0.277	0.342	0.560	0.634
DoF model	3	7	5	9
DoF residuals	41	37	25	21
RMSE	0.243	0.232	0.201	0.183
Obs./Parameters	11.3	5.6	5.2	3.1
SD residuals	0.2343207	0.21232	0.1835346	0.1533922
Max residual (negative)	-0.6307651	-0.647999	-0.4782766	-0.5049934
Max residual (positive)	0.4843418	0.4104114	0.3649711	0.2382828
Selected parameters				
Altitude	-0.00084***	-0.00059*	-0.00041	-0.00045
	(0.00025)	(0.00030)	(0.00038)	(0.00043)
Type of soil CLAY	0.22782**	0.32087**	-0.91930***	0.80511
	(0.08784)	(0.12035)	(0.23404)	(2.29508)
Type of soil SAND	0.23126*	-0.11786	0.21262**	-0.91692*
	(0.11799)	(0.18243)	(0.08328)	(0.48924)
Average annual Temperature		0.04776**		-0.03406
		(0.02247)		(0.11175)
Average annual precipitation - 2		-0.00073**		0.00183*
		(0.00033)		(0.00091)
Global aridity index		0.99780**		4.82165
		(0.38930)		(3.84751)
Width		0.01454*		0.02103**
		(0.00812)		(0.00983)
Input conc. TN			-0.00726*	-0.01747**
			(0.00362)	(0.00735)
Input conc. NO3			0.05949***	0.05100
			(0.01182)	(0.05821)

NBS B, BS-R – N-NO3 Linear Models	(1)	(2)	(3)	(4)
Constant	0.81356*** (0.05723)	-0.01391 (0.43960)	0.59982*** (0.10186)	-4.39261* (2.33810)

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.4.6 Selected model for Sediments removal of NBS, buffer strips for runoff interception

Model 2 performs much better in terms of almost all the statistical indicators. SED loading rate is not significant, and its inclusion slightly worsens the goodness of fit of the model given by the R2 adjusted. However, the robustness of the model is much lower owing to the reduced sample (just 3.3 observations/parameter), so Model 3 could be chosen from a statistical perspective. However, the R2 of model (3) is low and with the selected variable not in line with literature. According to Vidon et al. (2019), BS-Rs perform better in high-infiltration soils, therefore a positive effect of soils with sand would be expected, while the sign is the opposite in model (3). Therefore, it is suggested not to use any of the proposed linear models for the favourability and opportunities maps. If the BS-R is placed in optimal functioning conditions and with dimensions in line with the literature range of design variables, the median removal performance (50^{th} percentile) can be assumed.

Table 19. Detailed results of multiple linear regression for NBS B, BS-Rs (buffer strip for surface runoff interception), for sediments. Heteroskedastic robust standard errors in parentheses. None of the statistical model is selected.

NBS B, BS-R – Sediments Linear Models	(1)	(2)	(3)	(4)
Goodness of fit indexes				
Observations	26	26	26	26
R-squared	0.28826	0.81919	0.34573	0.82105
R2 adjusted	0.226	0.734	0.257	0.72
DoF model	1	7	2	8
DoF residuals	23	17	22	16
RMSE	0.116	0.0683	0.114	0.07
Obs./Parameters	13.0	3.3	8.7	2.9
SD residuals	0.1117126	0.0563048	0.1071074	0.0560156
Max residual (negative)	-0.306446	-0.151564	-0.2899978	-0.1478107
Max residual (positive)	0.2074033	0.0941792	0.2242257	0.0966467
Selected parameters				
Altitude	-0.00058* (0.00029)	-0.00040** (0.00015)	-0.00054* (0.00029)	-0.00048*** (0.00016)
Type of soil SAND	-0.18266*** (0.03361)	0.27628 (0.20911)	-0.14433*** (0.02868)	0.12923 (0.24668)
Surface slope		0.04536** (0.01770)		0.03991*** (0.01188)
Average annual Temperature		-0.24133*** (0.07328)		-0.23018*** (0.05588)
temporal uniformity of precipitation pattern (standard deviation)		-1.29407*** (0.35952)		-1.23137*** (0.26374)
Average annual precipitation - 2		0.00453*** (0.00123)		0.00460*** (0.00126)
Global aridity index		-6.34106*** (1.77815)		-6.17960*** (1.46241)
Width		0.01689***		0.01701***

NBS B, BS-R – Sediments Linear Models	(1)	(2)	(3)	(4)
		(0.00348)		(0.00367)
Input conc. Sed			0.00000 (0.00000)	-0.00000 (0.00001)
Constant	1.04386*** (0.06521)	5.14042*** (1.24900)	0.99934*** (0.05663)	4.85260*** (0.88793)

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.4.7 Selected model for TSS removal of NBS, buffer strips for runoff interception

The TSS loading rate is significant and its inclusion does not reduce the sample size. Models (3) and (4) perform similarly, but the latter has slightly better performance and is hence preferred. However, the negative effect of soils with sand is not in agreement with expert-based judgment, for the same reasons as sediment models. Therefore, it is suggested not to use any of the proposed linear models for the favourability and opportunities maps. If the BS-R is placed in optimal functioning conditions and with dimensions in line with the literature range of design variables, the median removal performance (50th percentile) can be assumed.

Table 20. Detailed results of multiple linear regression for NBS B, BS-R (buffer strip for surface runoff interception), for N-NO3. Heteroskedastic robust standard errors in parentheses. None of the statistical model is selected.

NBS B, BS-R – TSS Linear Models	(1)	(2)	(3)	(4)
Goodness of fit indexes				
Observations	28	28	28	28
R-squared	0.41347	0.46682	0.49081	0.51782
R2 adjusted	0.367	0.400	0.427	0.434
DoF model	2	3	3	4
DoF residuals	25	24	24	23
RMSE	0.0950	0.0924	0.0903	0.0898
Obs./Parameters	9.3	7.0	7.0	5.6
SD residuals	0.0913873	0.087132	0.08514	0.08286
Max residual (negative)	-0.2100074	-0.2030919	-0.1853441	-0.1844051
Max residual (positive)	0.138567	0.131058	0.1413893	0.1423282
Selected parameters				
Altitude	-0.00019* (0.00011)	-0.00024** (0.00011)	-0.00018* (0.00010)	-0.00022* (0.00011)
Type of soil SAND	-0.26610*** (0.06883)	-0.27476*** (0.06422)	-0.33864*** (0.04024)	-0.33349*** (0.03951)
Global aridity index		-0.13972** (0.05224)		-0.10295* (0.05392)
Input conc. TSS			0.00000** (0.00000)	0.00000* (0.00000)
Constant	0.96863*** (0.04362)	1.09852*** (0.07214)	0.93479*** (0.04408)	1.03588*** (0.07392)

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.4.8 General considerations on the results of multiple linear regression analysis *for NBS B, buffer strips for subsurface groundwater interception (BS-Gs)*

Because of the lack of an adequate sample size, the analysis of subterranean buffer strips was conducted on only one contaminant, i.e. NO3, which is the main target of buffer strips for groundwater interception (Vidon et al., 2019; Stutter et al., 2019; Hill 2019). Despite a vast dataset (n° 107 samples), the models are able to explain only a small part of the variability of the abatement efficiency (**Table 21**). This is in line with expert-based judgment and literature. The main explanation is that buffer strips for groundwater interception from peer review literature are often monitored under optimal functioning conditions, as also reported by Gold et al. (2001). This is clear for the key variable for BS-G positioning, i.e. the water table depth: the optimal suggested value by Dosskey and Qiu (2011) is less than 2 m and the 3rd quartile of NBS BS-G dataset is 2.5 m, i.e. the samples were probably not sufficient to capture the detrimental effect of too deep water tables with linear regression. Similar considerations can also be made for the width: Hill (2018) reviewed several studies and found that usually a width of less than 20 m for a BS-G placed where the water table is shallow is sufficient to reach 90% of nitrate removal efficiency. The median width (50th percentile) for BS-Gs is 12 m in the built dataset; the 3rd quartile (75th percentile) is 31 m. Basically, the BS-G sampled from peer review literature worked under optimal conditions and the frequency density function of the percentage removal fits well the literature data (see **Errore. L'origine riferimento non è stata trovata.**), with a median removal efficiency of 58%. These issues are similar to those encountered by similar studies, such as Mayer et al. (2007), who also found many typical design variables not relevant or relevant with low fitting performance, such as width and vegetation. <u>As a result, the fitted models have a too low R2 and it is suggested not to use any of them for the favourability and opportunities maps. If the BS-G is placed in optimal functioning conditions, the median removal performance (50th percentile) can be assumed</u>.

Table 21. Detailed results of multiple linear regression for NBS B, BS-Gs (buffer strip for subsurface groundwater interception), for N-NO3. Heteroskedastic robust standard errors in parentheses. None of the statistical model is selected.

NBS B, BS-G – N-NO3 Linear Models	**(1)**	**(2)**	**(3)**	**(4)**
Goodness of fit indexes				
Observations	107	107	106	106
R-squared	0.03775	0.05309	0.05117	0.06466
R2 adjusted	0.0192	0.0255	0.0233	0.0276
DoF model	2	3	3	4
DoF residuals	104	103	102	101
RMSE	0.759	0.756	0.759	0.757
Obs./Parameters	35.7	26.8	26.5	21.2
SD residuals	0.7513933	0.7453835	0.7477442	0.7424085
Max residual (negative)	-5.359615	-5.343726	-5.341241	-5.327528
Max residual (positive)	0.7894552	0.802735	0.8022572	0.8139107
Selected parameters				
Type of soil CLAY	0.30480	0.28653	0.18985	0.17935
	(0.20809)	(0.20633)	(0.20349)	(0.20147)
Type of soil SAND	0.31068	0.25472	0.26719	0.21786
	(0.21533)	(0.21128)	(0.21259)	(0.20886)
Width		0.00261**		0.00245**
		(0.00106)		(0.00105)
Input conc. NO3			0.00539	0.00502*
			(0.00336)	(0.00302)
Constant	0.20810	0.16873	0.18795	0.15233
	(0.21290)	(0.21630)	(0.21586)	(0.21858)

*** p<0.01, high significance; ** p<0.05, medium significance, * p<0.1, significance

2.1.1.5 Summary of selected models

This section summarizes the selected models in the following tables:

- NBS A **Table 22**
- NBS B, VDDs and wetlands **Table 23**
- NBS B, BS-Rs **Table 24**

which should be applied, as predictive models, as follows

$$\eta = \sum_i a_i v_{b,i} + \sum_j b_j v_{c,j} + c$$

where:

- η removal efficiency of the targeted pollutant, variable from 0 to 1 (0-100%)
- $v_{b,i}$ *i*-th binary variable, equal to either 0 (no) or 1 (yes)
- a_i multiplicative linear coefficient of the *i*-th binary variable
- $v_{c,j}$ *j*-th cardinal variable, expressed with the selected unit
- b_j multiplicative linear coefficient of the *j*-th binary variable
- c linear intercept of the multiple regression linear model

The linear models for the remaining pollutants and NBS were judged negatively by experts and it is suggested not to use any of the proposed linear models for the favourability and opportunity maps. If the NBS are placed in optimal functioning conditions and with size in line with literature range of design variables, the median removal performance (50th percentile) can be assumed as follows:

- NBS B, vegetated drainage ditches (VDDs) and wetlands
  - P-PO4 40% (17 samples, **Errore. L'origine riferimento non è stata trovata.**)
- NBS B, buffer strips for surface runoff interception
  - TN 70% (52 samples, **Errore. L'origine riferimento non è stata trovata.**)
  - N-NO3 70% (51 samples, **Errore. L'origine riferimento non è stata trovata.**)
  - P-PO4 80% (36 samples, **Errore. L'origine riferimento non è stata trovata.**)
  - TSS 90% (28 samples, **Errore. L'origine riferimento non è stata trovata.**)
  - Sediments 90% (48 samples, **Errore. L'origine riferimento non è stata trovata.**)
- NBS B, buffer strips for subsurface groundwater interception
  - N-NO3 60% (111 samples, **Errore. L'origine riferimento non è stata trovata.**)

Table 22. Selected linear models for NBS A, manure-driven wastewater. Selected models: (1) multiple linear regression with variables selected by MCorA, without the influent loads; (2) multiple linear regression with variables selected by MCorA, with the influent loads; (3) multiple linear regression with all variables, without the influent loads; (4) multiple linear regression with all variables selected by MCorA, without the influent loads.

NBS A	Category	Type	Unit	TN Model (3)	TP Model (4)	TKN Model (1)	BOD5 Model (1)	COD Model (1)	TSS Model (2)
Goodness of fit indexes									
Observations				31	32	14	21	19	22
R2				0.695	0.494	0.578	0.809	0.544	0.631
R2 adjusted				0.603	0.397	0.39	0.776	0.487	0.544
DoF model				5	4	4	3	2	3
DoF residuals				23	26	9	17	16	17
RMSE				0.162	0.201	0.16	0.120	0.183	0.165
Obs./Parameters				4.43	5.33	2.33	4.20	4.75	4.40
Max residual (positive)				0.250	0.474	0.228	0.216	0.311	0.233
Max residual (negative)				-0.371	-0.419	-0.223	-0.235	-0.495	-0.401
SD residuals				0.141	0.185	0.133	0.110	0.173	0.148
Selected parameters				**Multiplicative linear coefficients**					
Average annual Temperature	Climate	Cardinal	°C				-0.04177		
Average annual precipitation	Climate	Cardinal	cm/year	0.00154					
ww_mix_RNF	Landscape	Binary	-	-0.28044		-0.22470	0.16764		-0.07168
ww_Poultry	Landscape	Binary	-	-0.33049					
Specific water inflow	Landscape	Cardinal	1000 m^3 y^{-1} ha^{-1}	-0.00019	0.00008	-0.00010	-0.00027	-0.00028	
Previous treatment Primary NBS	Design	Binary	-			-0.19523		-0.21592	
Previous treatment Primary NBS + Secondary NBS	Design	Binary	-	-0.29820	-0.39422	-0.34926			
Previous treatment Primary grey	Design	Binary	-						0.39646
Area	Design	Cardinal	ha		0.36330				
Filling media Porous media + soil	Design	Binary	-	0.24817					0.36227
Type of aquatic vegetation Emergent	Design	Binary	-	-0.25072	-0.52466				
Total Nitrogen loading rate	Design	Cardinal	t_N y^{-1} ha^{-1}						
Total Phosphorous loading rate	Design	Cardinal	t_P y^{-1} ha^{-1}		-0.07098				
Solid loading rate	Design	Cardinal	t_{SS} y^{-1} ha^{-1}						-0.00038
Linear intercept				0.75637	1.16845	0.74648	1.16629	0.85499	0.54407

Table 23. Selected linear models for NBS B, diffuse pollution control with vegetated drainage ditches (VDDs) and wetlands. Selected models: (1) multiple linear regression with variables selected by MCorA, without the influent loads; (2) multiple linear regression with variables selected by MCorA, with the influent loads; (3) multiple linear regression with all variables, without the influent loads; (4) multiple linear regression with all variables selected by MCorA, without the influent loads.

NBS B, VDDs and wetlands	**Category**	**Type**	**Unit**	**TN Model (1)**	**N-NO3 Model (2)**	**TP Model (3)**
Goodness of fit indexes						
Observations				73	42	39
R2				0.26467	0.67481	0.44579
R2 adjusted				0.233	0.630	0.381
DoF model				3	5	3
DoF residuals				69	36	34
RMSE				0.261	0.168	0.339
Obs./Parameters				18.3	7.0	9.8
Max residual (positive)				0.4993604	0.252	0.5688084
Max residual (negative)				-0.6366287	-0.522	-1.057382
SD residuals				0.2555567	0.158	0.3210826
Selected parameters				**Multiplicative linear coefficients**		
Average annual precipitation	Climate	Cardinal	mm y^{-1}	0.00087		
Average annual n of days with T < threshold C	Climate	Cardinal	n° months y^{-1}		-0.04549	
Temporal uniformity of precipitation pattern	Climate	Cardinal	-		-0.09511	
Global aridity index (adj)	Climate	Cardinal	-	-1.12099	-0.53846	
Potential annual evapo-transpiration	Climate	Cardinal	mm y^{-1}	-0.00039		-0.00029
Type VDD	Design	Binary	-		0.16621	
Aspect-Ratio	Design	Cardinal	-			0.00186
Type of aquatic vegetation Emergent	Design	Binary	-			0.72074
Substrate	Design	Binary	-			0.47749
TN loading rate	Design	Cardinal	t_N y^{-1} ha^{-1}			
N-NO3 loading rate	Design	Cardinal	t_P y^{-1} ha^{-1}		-0.00924	
Linear intercept				0.98180	1.27037	-0.08845

Table 24. Selected linear models for NBS B, diffuse pollution control with buffer strips for surface runoff interception (BS-Rs). Selected models: (1) multiple linear regression with variables selected by MCorA, without the influent loads; (2) multiple linear regression with variables selected by MCorA, with the influent loads; (3) multiple linear regression with all variables, without the influent loads; (4) multiple linear regression with all variables selected by MCorA, without the influent loads.

NBS B, BS-Rs	**Category**	**Type**	**Unit**	**TP Model (2)**
Goodness of fit indexes				
Observations				37
R-squared				0.6371
R2 adjusted				0.565
DoF model				5
DoF residuals				30
RMSE				0.125
Obs./Parameters				6.2
SD residuals				0.1145418
Max residual (negative)				-0.2730779
Max residual (positive)				0.1971332
Selected parameters				**Multiplicative linear coefficients**
Average annual Temperature	Climate	Cardinal	°C	0.04093
Average annual precipitation	Climate	Cardinal	mm y^{-1}	-0.00161
Global aridity index	Climate	Cardinal	-	1.15638
Type of soil CLAY	Landscape	Binary	-	0.16350
Width	Design	Cardinal	m	0.02620
Type Herbaceous	Design	Binary	-	0.77568
Linear intercept				-0.18858

2.1.1.6 Verification of equations

To verify the equations obtained with the results of the statistical analysis, a comparison was made between the selected linear fitted model and some benchmark literature models. The removal percentages of each contaminant are calculated using the equations with the variables obtained from the statistical analysis and the parameters (climate, landscape and design) from the dataset. The results are then compared with the percentages of removal found in the collected database and with the percentages obtained with literature models. The following literature models were used:

- Wetlands
  - kinetic models proposed by Reed et al. (1995) for BOD5, COD, TP, N-NO3
  - P-k-C* models by Kadlec and Wallace (2009), testing both the 50th and 70th percentile kinetic parameters for BOD5, COD, TN, TP, N-NO3
- Buffer strips for surface runoff interception (BS-R)
  - fitting models proposed by Zhang et al. (2010) for TP, TN, and sediments

The goodness of fit is studied with (i) goodness of fit indexes, (ii) statistical frequency density functions of errors, (iii) and graphical representation with "Predicted vs. Actual" graphs. All the details are reported in the following sections.

2.1.1.6.1 Verification of the selected linear model with literature models of NBS A

The NBS A dataset (Attachment 1) was used to estimate the accuracy of the literature models proposed by Kadlec and Wallace (2009) and Reed et al. (1995), in comparison to the fitted linear model. Results are visible in **Table 25** and **Figure 1**.

It can be noted that the results obtained from the literature models are more dispersive than those obtained with the fitted linear model, which, apart from some isolated cases, remain fairly close to the bisector, indicating that the values obtained with the fitting are closer to the actual values. This is also confirmed by the indexes and the error frequency density function:

- R2 is always higher for the linear fitting model in comparison to the literature models;
- the standard deviation of the residuals and median (50th percentile) of the errors is always lower for the linear fitting model in comparison to the literature models.

In particular, it can be observed from **Figure 1** that the dots corresponding to the values obtained from the models are mostly to the right of the bisector, indicating that these models tend to overestimate the pollutant removal efficiencies, while the dots corresponding to the fitting are more evenly placed. This is to be expected, since both the literature models of Kadlec and Wallace (2009) and Reed et al. (1995) are mainly fitted on domestic/municipal wastewater datasets, which have on average influent pollutant concentrations lower than the manure-driven one. Therefore, it seems that this kind of equations tends to overestimate removal performance with concentrations higher than the usual range of domestic/municipal wastewater.

The verification analysis suggests that the fitted linear models are better suited to approximate the observed data for NBS A than the models from literature and are recommended for developing the favourability and opportunity maps for NBS A.

Table 25. Results of the verification of the linear fitting model (L) with the literature models (K_50th, Kadlec and Wallace, 2009, kinetic with 50th percentile; K_70th, Kadlec and Wallace, 2009, kinetic with 70th percentile; R, Reed et al., 1995) for NBS A, wetlands for manure-driven wastewater

NBS A	**BOD**				**COD**				**TN**			**TP**				**TKN**		
	L	**K_50th**	**K_70th**	**R**	**L**	**K_50th**	**K_70th**	**R**	**L**	**K_50th**	**K_70th**	**L**	**K_50th**	**K_70th**	**R**	**L**	**K_50th**	**K_70th**
Goodness of fit indexes																		
Observations	21	18	18	15	19	11	11	9	31	23	23	32	23	23	24	14	14	14
R2	0.809	0.350	0.310	0.153	0.544	0.426	0.410	0.192	0.695	0.384	0.365	0.494	0.215	0.171	0.199	0.578	0.297	0.305
RMSE	0.120	0.241	0.285	0.360	0.183	0.270	0.330	0.420	0.162	0.323	0.384	0.201	0.382	0.438	0.421	0.160	0.301	0.335
Max residual (positive)	0.216	0.211	0.025	0.003	0.311	0.127	-0.003	-0.057	0.250	0.122	0.028	0.474	0.252	0.217	0.252	0.228	0.103	0.083
Max residual (negative)	-0.235	-0.710	-0.789	-0.919	-0.495	-0.479	-0.529	-0.659	-0.371	-0.737	-0.742	-0.419	-0.754	-0.786	-0.794	-0.223	-0.619	-0.639
SD residuals	0.110	0.209	0.207	0.251	0.173	0.220	0.199	0.230	0.141	0.230	0.224	0.185	0.277	0.280	0.281	0.133	0.230	0.220
Statistical analysis frequency density function of errors																		
mean - error	0%	13%	20%	27%	0%	17%	27%	36%	0%	23%	32%	0%	27%	34%	32%	0%	20%	26%
std - error	11%	21%	21%	25%	17%	22%	20%	23%	14%	23%	22%	18%	28%	28%	28%	13%	23%	22%
min - error	-22%	-21%	-3%	0%	-31%	-13%	0%	6%	-25%	-12%	-3%	-47%	-25%	-22%	-25%	-23%	-10%	-8%
25th perc - error	-5%	-2%	3%	6%	-10%	-3%	7%	16%	-10%	6%	16%	-12%	3%	12%	8%	-7%	1%	8%
50th perc - error	-1%	8%	22%	26%	-6%	18%	32%	43%	-1%	24%	26%	0%	35%	40%	40%	1%	21%	24%
75th perc - error	1%	22%	28%	37%	8%	33%	44%	54%	5%	38%	50%	11%	48%	56%	55%	7%	29%	38%
max - error	23%	71%	79%	92%	49%	48%	53%	66%	37%	74%	74%	42%	75%	79%	79%	22%	62%	64%

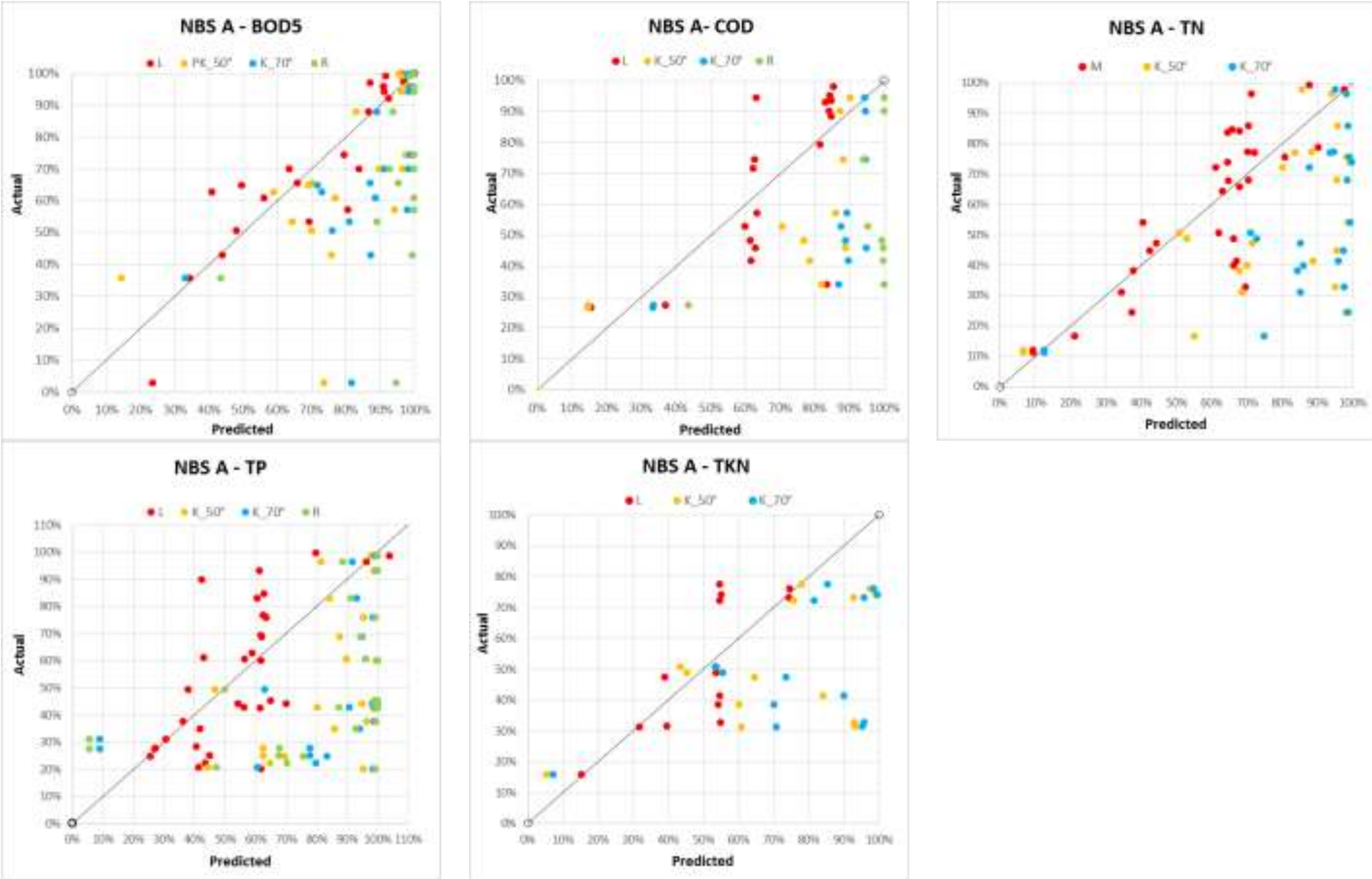

Figure 1. Predicted vs. Actual graphs for linear fitted (L) with literature models (K_50th, Kadlec and Wallace, 2009, kinetic with 50th percentile; K_70th, Kadlec and Wallace, 2009, kinetic with 70th percentile; R, Reed et al., 1995) for NBS A, wetlands for manure-driven wastewater

2.1.1.6.2 Verification of the selected linear model with literature models of NBS B, wetlands and VDDs

The NBS B dataset for VDDs and wetlands (Attachment 2) was used to estimate the accuracy of the literature models proposed by Kadlec and Wallace (2009) and Reed et al. (1995), in comparison to the fitted linear model. The results are visible in **Table 26** and **Figure 2**.

It can be noted that the results obtained from the literature models are more dispersive than those obtained with the fitted linear model, which, apart from some isolated cases, remain fairly close to the bisector, indicating that the values obtained with the fitting are closer to the actual values. This is also confirmed by the indexes and error frequency density function:

- R2 is always higher for the linear fitting model in comparison to the literature models;
- the standard deviation of the residuals and median (50^{th} percentile) of errors is always lower for the linear fitting model in comparison to the literature models.

The verification analysis suggests that the fitted linear models are better suited to approximate the observed data for NBS B – VDDs and wetlands – than the models from literature and are recommended for developing the favourability and opportunity maps for NBS B.

Table 26. Results of the verification of the linear fitting model (L) with the literature models (K_50^{th}, Kadlec and Wallace, 2009, kinetic with 50^{th} percentile; K_70^{th}, Kadlec and Wallace, 2009, kinetic with 70^{th} percentile; R, Reed et al., 1995) for NBS B, vegetated drainage ditches (VDDs) and wetlands for diffuse pollution.

NBS B	VDD and wetland, N-NO3				VDD and wetland, TN			VDD and wetland, TP			
	L	K_50^{th}	K_70^{th}	R	L	K_50^{th}	K_70^{th}	L	K_50^{th}	K_70^{th}	R
Goodness of fit indexes											
Observations	42	38	38	38	73	45	45	39	29	29	30
R2	0.6748	0.053	0.057	0.106	0.26467	0.213	0.252	0.44579	0.00003	0.00268	0.0000003
RMSE	0.168	0.377	0.371	0.385	0.261	0.302	0.302	0.339	0.526	0.575	0.536
Max residual (positive)	0.252	0.897	0.611	0.681	0.499	0.709	0.709	0.569	0.814	0.805	0.814
Max residual (negative)	-0.522	-0.585	-0.872	-0.657	-0.637	-0.507	-0.507	-1.057	-1.315	-1.452	-1.338
SD residuals	0.158	0.373	0.375	0.387	0.256	0.302	0.302	0.321	0.532	0.601	0.538
Statistical analysis frequency density function of errors											
mean - error	0%	-9%	4%	5%	0%	-13%	-5%	6%	14%	9%	6%
std - error	16%	37%	37%	39%	26%	29%	30%	53%	57%	54%	53%
min - error	-25%	-90%	-61%	-68%	-50%	-73%	-71%	-81%	-81%	-81%	-81%
25^{th} perc - error	-15%	-22%	-10%	-19%	-18%	-29%	-21%	-35%	-29%	-34%	-35%
50^{th} perc - error	2%	-1%	-6%	3%	1%	-14%	-6%	-2%	4%	0%	-2%
75^{th} perc - error	11%	5%	16%	38%	17%	1%	17%	41%	50%	42%	41%
max - error	52%	59%	87%	66%	64%	48%	51%	131%	145%	134%	131%

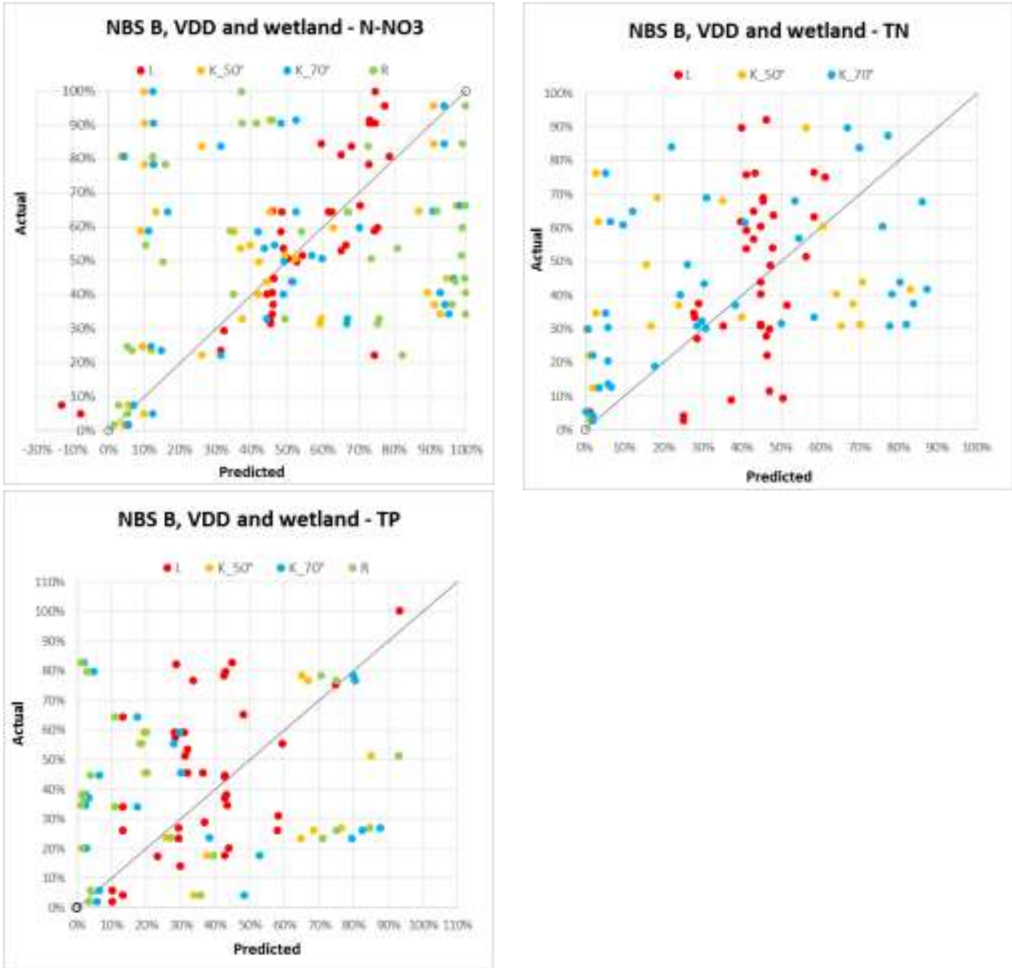

Figure 2. Predicted vs. Actual graphs for linear fitted (L) with literature models (K_50th, Kadlec and Wallace, 2009, kinetic with 50th percentile; K_70th, Kadlec and Wallace, 2009, kinetic with 70th percentile; R, Reed et al., 1995) for NBS B, vegetated drainage ditches (VDDs) and wetlands for diffuse pollution

2.1.1.6.3 Verification of the selected linear model with literature models of NBS B, buffer strips for runoff interception

The NBS B dataset for buffer strips (Attachment 3) was used to estimate the accuracy of the literature model proposed by Zhang et al. (2010), in comparison to the fitted linear model for BS-R. Results are visible in **Table 27** and **Figure 3**.

It can be noted that the results obtained from the literature model are more dispersive than those obtained with the fitted linear model, which, apart from some isolated cases, remain fairly close to the bisector, indicating that the values obtained with the fitting are closer to the actual values. This is also confirmed by the indexes and error frequency density function:

- R2 is always higher for the linear fitting model in comparison to the literature model;
- the standard deviation of the residuals and median (50th percentile) of errors is always lower for the linear fitting model in comparison to the literature models.

The verification analysis suggests that the fitted linear models are better suited to approximate the observed data for NBS B – buffer strips for runoff interception – than the models from literature and are recommended for developing the favourability and opportunity maps for NBS B.

Table 27. Results of the verification of the linear fitting model (L) with the literature model (Z, Zhang et al, 2010) for NBS B, buffer strips for surface runoff interception (BS-R) for diffuse pollution.

NBS B, BS-R	TP		TN		Sediments	
	L	Z	L	Z	L	Z
Goodness of fit indexes						
Observations	37	37	26	26	26	26
R2	0.637	0.190	0.361	0.351	0.346	0.026
RMSE	0.125	0.224	0.166	0.161	0.114	0.202
Max residual (positive)	-0.273	0.226	0.155	0.159	0.107	0.196
Max residual (negative)	0.197	-0.931	-0.4223	-0.398	-0.290	-0.570
SD residuals	0.115	0.298	0.210	0.2318	0.224	0.480
Statistical analysis frequency density function of errors						
mean - error	6.36%	-17.42%	3.79%	-3.77%	-3.20%	-6.26%
std - error	22.44%	35.02%	16.06%	15.93%	11.20%	19.56%
min - error	-19.37%	-93.11%	-17.18%	-23.18%	-22.99%	-47.98%
25^{th} perc - error	-5.37%	-29.75%	-8.30%	-14.56%	-9.45%	-11.73%
50^{th} perc - error	2.96%	-5.12%	1.81%	-9.05%	-5.22%	-6.33%
75^{th} perc - error	7.89%	11.26%	13.80%	3.36%	-1.96%	-1.88%
max - error	86.42%	27.43%	52.96%	39.81%	28.40%	57.04%

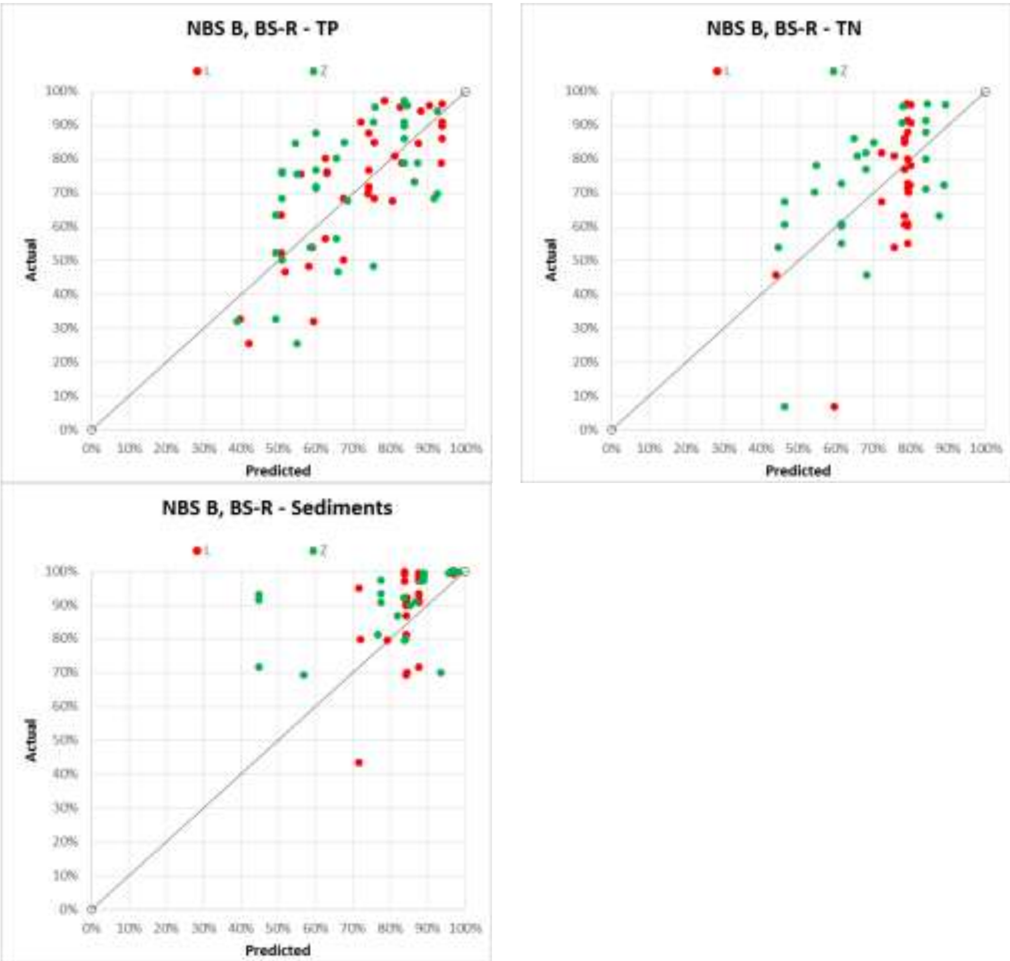

Figure 3. Predicted vs. Actual graphs for linear fitted (L) with literature model (Z, Zhang et al., 2010) for NBS B, buffer strips for surface runoff interception (BS-R) for diffuse pollution

2.1.2 Main benefits: Expert-based for pesticide removal of NBS B

The analysis of the effects of NBS on the reduction of agricultural-based pesticide pollution was carried out by reviewing the peer reviewed literature found on SCOPUS during the data mining activity (section **Errore. L'origine riferimento non è stata trovata.**), starting with the articles tagged as related to pesticides (see Annex 7).

The first comprehensive work on pesticide removal of NBS was the meta-analysis done in the review paper by Stehle et al. (2011). This work follows a similar approach to the one proposed for other pollutants in this work: (i) the development of a dataset of pesticide removal efficiencies of wetlands and vegetated drainage ditches based on a detailed literature analysis; (ii) a multiple linear regression analysis to assess which design and physicochemical properties of the pesticide (which can be interpreted as a landscape variable) could affect pesticide removal performance. Among the sixteen variables investigated, the relevant ones were, from greater to lesser relative importance: K_{OC}, organic carbon sorption coefficient (39.3% relative importance), percentage of plant coverage (34.9%); DT_{50}, time for the dissipation of 50% of the pesticide in water phase (13.4%); type of exposure (i.e. field or experimental monitoring – 9.9%); HRT, hydraulic retention time (2.5%). However, the multiple linear regression resulted in a low R2, equal to 0.193, which suggests a scarce capability of these selected variables to explain the high variability of performance and, therefore, not to use this linear model to predict the efficiency of wetlands and vegetated drainage ditches in pesticide removal. On the other hand, the study by Stehle et al. (2011) was the first review study indicating that one of the key variables in pesticide retention for an NBS with suitable design variables (e.g., HRT, HLR) is $\mathbf{K_{OC}}$, the **organic carbon sorption coefficient**. This indication also emerges from more recent review works by Vymazal and Březinová (2015) and Tournebize et al. (2017) for wetlands and vegetated drainage ditches, and Arora et al. (2010) for buffer strips. Indeed, the Koc describes the intrinsic behaviour of a compound to adsorb onto the organic matter. When the Koc of a molecule is less than 100 (log Koc <2) it shows low affinity for the organic matter and, consequently, a hydrophilic behaviour. These types of pesticides are likely to be found in higher concentrations in surface water. On the other hand, pesticides with a Koc between 100 and 1000 (2< log Koc < 3) adsorb moderately on sediments while those with a Koc > 1000 (log Koc > 3) have a strong sorption (hydrophobic). This interpretation seems to be confirmed also by the variable pesticide removal efficiencies reported in literature as function of their chemical group, ranging from 20% (triazinone) to >90% (organochlorine), as reviewed by Vymazal and Březinová, (2015). It is significant to refer that similar results were reported by the recent review by Ilyas et al. (2020) on other emerging organic contaminants similar to pesticides, i.e. pharmaceutical. Although NBS removal processes (plant uptake, photodegradation, sorption, adsorption, and biodegradation) may affect pharmaceutical removal differently depending on the different targeted pollutant, an overall successful regression equation was fitted (R2 0.65) for the general NBS pharmaceutical removal when only the physico-chemical properties of the compound were considered (Koc, Dow – octanol-water distribution coefficient - and molecular weight). Weaker and more incongruent correlations, on the other hand, were observed for typical design parameters, such as hydraulic retention time (HRT), hydraulic and organic loading rate (HLR and OLR, respectively).

In accordance with the previously described literature evidence, a simplified approach is proposed to estimate pesticide removal effectiveness and support the development of the favourability and opportunity maps.

First, four **specific datasets** (see Attachment 4) were developed by reviewing the literature tagged as "pesticide" in the data mining activity (section **Errore. L'origine riferimento non è stata trovata.**):

— pesticide removal in vegetated drainage ditches (VDDs), n° of samples 32;

— pesticide removal in wetlands, n° of samples 73;

— pesticide removal in buffer strips for surface runoff interception (BS-R), n° of samples 100;

— pesticide removal in buffer strips for subsurface groundwater interception (BS-G), n° of samples 84.

The datasets were used to define the frequency density functions of pesticide removal efficiency for three classes of organic carbon sorption coefficient: (i) log Koc <2; (ii) 2< log Koc < 3; (iii) log Koc > 3, in accordance with the analysis proposed by the review work by Tournebize et al. (2017). The results are visible in **Figure 8** and **Table 28**, from which the following key results can be highlighted:

— median efficiency rates of vegetated drainage ditches were equal to 50.5% and 84.0% for moderately and strongly sorbed pesticides, respectively;

— The results obtained for wetlands show that weakly sorbed pesticides are poorly removed (median=41.9%) compared to the moderately (median= 61.2%) and strongly (84.0%) sorbed pesticides. It is important to notice that the removal of pesticides is highly variable. For instance, the efficiencies for weakly sorbed pesticides vary between 3% and 94%.

— Weakly sorbed pesticides showed a lower median value (69.6%) also for buffer strips for surface runoff interception, easily reaching water bodies. The median removal efficiency of moderately and strongly sorbed pesticides is 80.9% and 83.1%, respectively. These last two Koc classes both have quite a high removal efficiency even if the difference between their medians is not statistically relevant.

— Data on pesticide removal of buffer strips for groundwater interception are scarce since investigations on this topic are quite recent, however it was found that in groundwater there is no difference between the removal of weakly and strongly sorbed pesticides. Indeed, the median removal for weakly adsorbed pesticides is 45% and 41% for strongly adsorbed pesticides.

If the NBS are placed in optimal functioning conditions and with dimensions in line with the literature range of design variables, the median removal performance (50th percentile) can be assumed for the pesticide according to the K_{OC} class.

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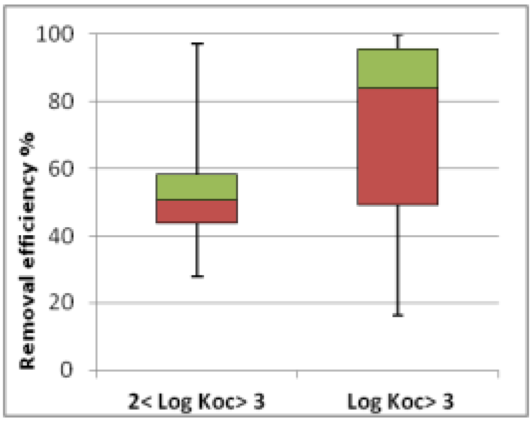
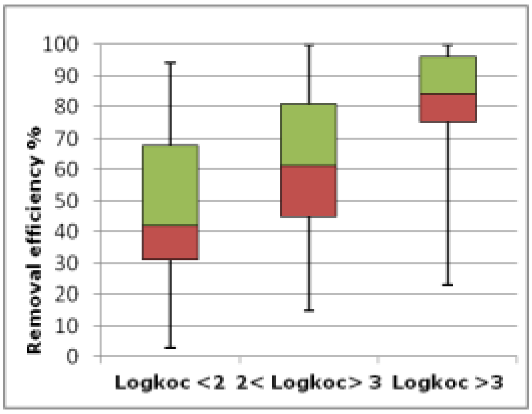
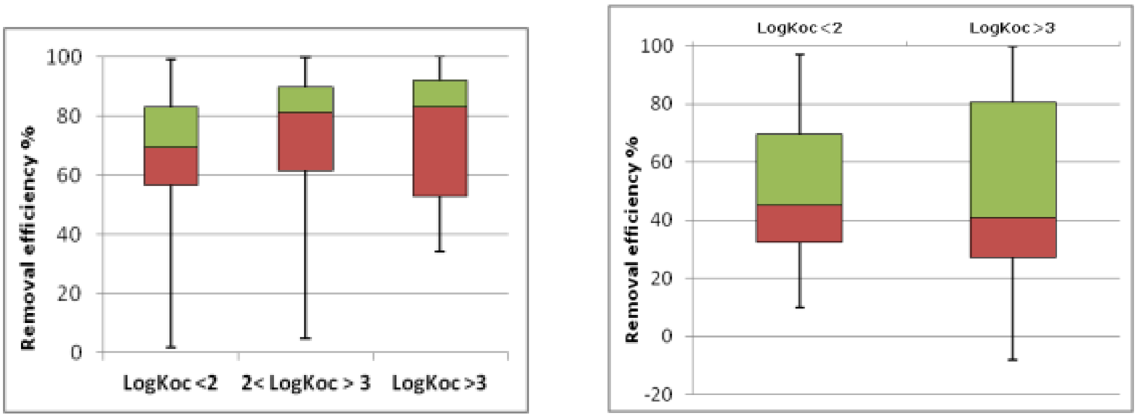


(a) VDD



(b) FWS wetland



(c) BS-R (d) BS-G

Figure 4. Box and whisker plots that correlate pesticide removal efficiencies with the 3 different classes of log Koc for: (a) vegetated drainage ditches (n° of samples 30); (b) free water surface wetlands (n° of samples 73); (c) buffer strips for surface runoff interception (n° of samples 100); (d) buffer strips for subsurface groundwater interception (n° of samples 81). The horizontal lines represent the medians.

Table 28. Statistical analysis of pesticide removal for the targeted NBS B.

	VDD			**FWS wetland**		
	logKoc<2	2<logKoc< 3	logKoc>3	logKoc<2	2<logKoc< 3	logKoc>3
Minimum		28.0%	16.3%	3.0%	15.0%	23.0%
1st quartile		44.0%	49.2%	31.1%	45.0%	75.0%
2nd quartile (median)		50.5%	84.0%	41.9%	61.2%	84.0%
3rd quartile		58.2%	95.5%	67.9%	81.0%	96.0%
max		97.0%	100.0%	94.2%	100.0%	100.0%
n° samples		10	20	20	32	21
	BS-R			**BS-G**		
	logKoc<2	2<logKoc< 3	logKoc>3	logKoc<2	2<logKoc< 3	logKoc>3
Minimum	1.8%	4.8%	34.0%	10.0%		-8.2%
1st quartile	56.6%	61.4%	53.0%	32.5%		27.0%
2nd quartile (median)	69.6%	80.9%	83.1%	45.0%		41.0%
3rd quartile	82.8%	89.6%	92.0%	69.7%		80.5%
max	99.0%	99.9%	100.0%	97.0%		100.0%
n° samples	28	48	24	19		62.0%

2.1.3 Main benefits: Expert-based for NBS C for droughts

2.1.3.1 General approach and NBS C categorization

The main target of NBS C group is the series of small NBS that can be diffused in the agriculture territory. The reference size is the same as those of the so-called "Farm Ponds" (Wisser et al. 2010), usually used to harvest the excess of runoff to use it, for instance, for emergency irrigation (e.g. Alvarez et al., 2008; Ibrahim and Amir-Faryar, 2018; Beckingham et al., 2019) or to sustain the aquifer through managed recharge (e.g., Teatini et al., 2015). Typical sizes range from 100 to 10000 m^2 (Ibrahim and Amir-Faryar, 2018).

The analysis of NBS C is based on the schematic representation given in **Figure 5**. The main assumption is that the NBS is included within a **catchment (grid) area of suitable size to develop a runoff to be intercepted**. The catchment also has a maximum size that is assumed to not interfere with the hydrological basin, in fact it is expected that the small-size farm ponds are spread within the agriculture territory and are not connected to the principal drainage paths of the hydrological basins (e.g. rivers and big streams). Substantially, the size of the studied NBS C is that of small interventions to retain the runoff within the territory, in agreement with the micro-pond concept defined in Salazar et al. (2012). The target, therefore, allows to neglect horizontal exchange of the runoff from grids, following the methodology proposed by Wisser et al. (2010) to estimate the potential role of farm ponds in supporting the irrigation of arid regions on a global scale. As a result, each grid can be divided between an area without NBS ($A_{NO\ NBS}$), which generates the runoff, and a potential area to intercept the runoff with NBS (A_{NBS}) if a suitable area is available.

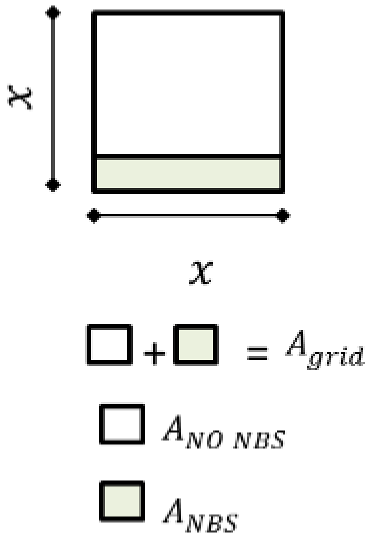


Figure 5. Schematization for NBS C analysis

On the basis of the previous assumptions, the expected performance of the NBS C on droughts is function of the **water budget at NBS area scale**, represented in **Figure 6**, which includes the following elements (e.g., Machiwal et al., 2017):

- R runoff from $A_{NO\ NBS}$
- P precipitation on A_{NBS}
- E/ET evaporation and/or evapotranspiration from A_{NBS}
- I infiltration on the bottom of the A_{NBS}
- D demand

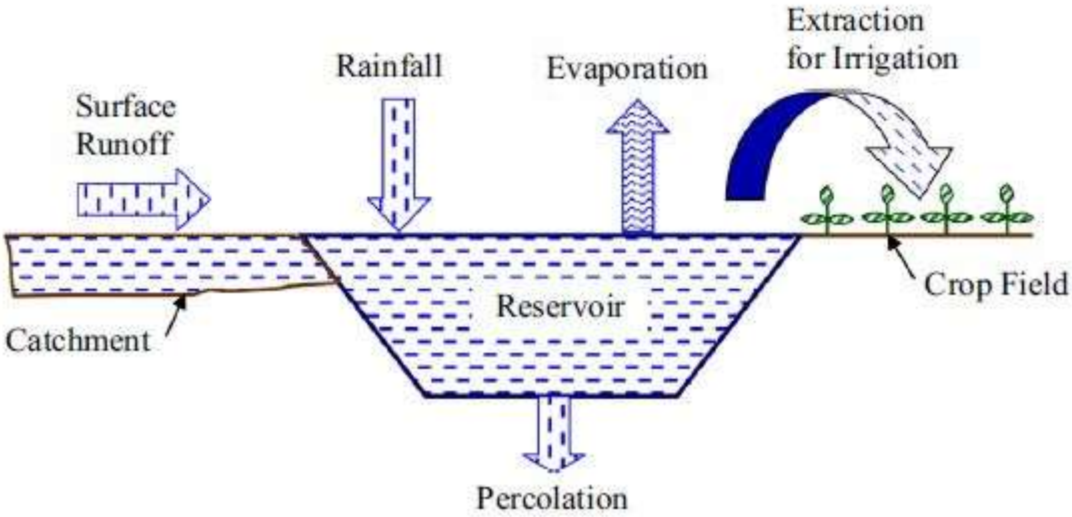


Figure 6. Water budget at NBS C scale

Source: Machiwal et al., 2017

The performance in terms of droughts is a function of the volume of the NBS and the resolution of the water budget. The European scale of the analysis, however, suggests avoiding the full resolution of the water budget for each grid and proposing simplified resolutions of the water budget itself, according to the main NBS targets, as well as design, landscape and climate features. To this aim, a set of potential NBS was defined for the two main design objectives to tackle the effects of drought events, i.e. storage, and infiltration (MAR – Managed Aquifer Recharge).

The categorization is reported in **Table 29**, including a summary of the main features that differentiate one NBS from the other. Particularly, the use of the pre-treatment stage is included to account for the additional benefits of NBS and to limit siltation effects (Mioduszewski and Waldemar, 2012).

If, on the one hand, this approach multiplies the number of NBS to be considered, on the other it allows to simplify the resolution of the water budget, avoiding heavy geo-referenced computation on a European scale. Indeed, the categorization of the NBS allows the use of simplified assumptions to solve the water budget, and to estimate the performance in responding to drought events with simplified proxies.

Table 29. Categorization of NBS C

NBS C category	Description	Features
NBS C1 - Storage		
C1.1.1	Storage pond (shallow)	• Smaller storage volume • Lower construction cost • Decrease over time of the storage volume for siltation
C1.1.2	Storage pond (deep)	• Greater storage volume • Higher construction cost • Decrease over time of the storage volume for siltation
C1.2.1	Pre-treatment pond + Storage pond (shallow)	• Smaller storage volume • Lower construction cost • Extra construction cost for pre-treatment • Minimum area required for pre-treatment • Pre-treatment with lower biodiversity value • No decrease over time of the storage volume for siltation due to pre-treatment
C1.2.2	Pre-treatment pond + Storage pond (deep)	• Greater storage volume • Higher construction cost • Extra construction cost for pre-treatment • Smaller area required for pre-treatment • Pre-treatment with lower biodiversity value • No decrease over time of the storage volume for siltation due to pre-treatment
C1.3.1	Pre-treatment wetland + Storage pond (shallow)	• Smaller storage volume • Lower construction cost • Extra construction cost for pre-treatment • Greater area required for pre-treatment • Pre-treatment with higher biodiversity value • No decrease over time of the storage volume for siltation due to pre-treatment
C1.3.2	Pre-treatment wetland + Storage pond (deep)	• Greater storage volume • Higher construction cost • Extra construction cost for pre-treatment • Higher area required for pre-treatment • Pre-treatment with higher biodiversity value • No decrease over time of the storage volume for siltation due to pre-treatment
NBS C2 – Infiltration (MAR)		
C2.1.a	Infiltration Pond (high infiltration)	• Pond with periodic maintenance to avoid the decrease of the infiltration capacity due to clogging • Higher operational and maintenance costs

NBS C category	**Description**	**Features**
		• Lower biodiversity value (shorter ponding time during the year)
C2.1.b	Infiltration Pond (low infiltration)	• Pond without periodic maintenance with limited infiltration capacity due to clogging • Lower operational and maintenance costs • Higher biodiversity value (longer ponding time during the year)
C2.2	Pre-treatment pond + Infiltration pond (high infiltration)	• Pre-treatment to avoid the decrease of the infiltration capacity due to clogging • Extra construction cost for pre-treatment • Lower operational and maintenance costs • Smaller area required for pre-treatment • Pre-treatment with lower biodiversity value
C2.3	Pre-treatment wetland + Infiltration pond (high infiltration)	• Pre-treatment to avoid the decrease of the infiltration capacity due to clogging • Extra construction cost for pre-treatment • Lower operational and maintenance costs • Greater area required for pre-treatment • Pre-treatment with higher biodiversity value
C2.4	Infiltration wooded area	• More naturalistic infiltration area with limited infiltration capacity due to clogging • Lower operational and maintenance costs • Side-benefits due to the presence of trees

2.1.3.2 Definition of Area – Volume relationships

The definition of the available NBS volume with simple **volume-area relationships** has always been one of the key focuses for farm ponds and small reservoirs in general. Several volume-area relationships have been developed in literature (Ibrahim and Amir-Faryar, 2018; Ghansah et al., 2018; Ogilvie et al., 2016; Rodrigues et al., 2012; Annor et al., 2009; Roost et al., 2008; Sawunyama et al., 2006; Liebe et al., 2005).

In order to test the validity of the available volume-area relationships, a **dataset** of dimensional parameters of farm ponds was created by reviewing the literature tagged during the data mining activity (section **Errore. L'origine riferimento non è stata trovata.**). The dataset (Attachment 6) is composed of the following items:

- Country
- Area of the farm pond (in m^2)
- Volume (in m^3)
- Height (in m)
- Slope
- Area of the watershed (in m^2)
- NBS to watershed ratio

Following the definition of farm ponds given by Alvarez et al. (2008) for the Mediterranean European context (Spain), data for both small (less than 3000 m^2) and large (less than 30000 m^2) farm ponds was collected. As explained in section 2.1.3.1, as the focus is on farm ponds outside the main hydrological river and stream network, small dams were excluded, whenever the paper makes the difference with our targeted farm ponds clear. Since papers on single farm ponds are not so common in scientific peer review literature, range values and statistical analyses from censuses of farm ponds at watershed scale were also included. Despite being aware of the bias included with this assumption, these data allowed to broaden the dataset and give a more comprehensive overview of the typical farm pond sizes.

The dataset is composed of 95 samples and the **statistical analysis** is summarised in **Table 30**. As stated by several censuses at watershed scale, the most widespread farm ponds are the small ones, also used in developed countries such as Spain (Alvarez et al 2008; Jlassi et al., 2016) and US (Berg et al., 2015; Ibrahim and Amir-Faryar, 2018). Interestingly, the median size of the area, about 700 m^2, is very close to the 500 m^2 assumed by Wisser et al. (2010) for the study of the potential application of farm ponds at global level. Accordingly, most of the volumes also fall within the range of small farm ponds (median 2500 m^3). The most common farm ponds are shallow (median 2.5 m), but farm ponds up to 8 meters have also been found, allowing for maximum storage volume while taking up minimal space.

Table 30. Statistical analysis of the dataset regarding the dimensional parameters of farm ponds

	Area (m^2)	**Volume (m^3)**	**Height (m)**
Mean	3906	6687	3.0
Standard dev.	6697	8381	1.8
Min	60	32	1.0
Percentile 0.25	310	741	2.0
Percentile 0.50 (Median)	691	2500	2.5
Percentile 0.75	4875	10692	3.4
Max	30000	32400	8.1

	Area (m^2)	Volume (m^3)	Height (m)
n° samples	61	53	42

The comparison of the volume-area relationships with data from the dataset is shown in **Figure 7**, where is visible that the available relationships are not suitable for the farm pond scale. This is principally due to the fact that volume-area relationships are often developed for small reservoirs of larger sizes, typically small dams which lead to the typical triangular shape of the storage volume.

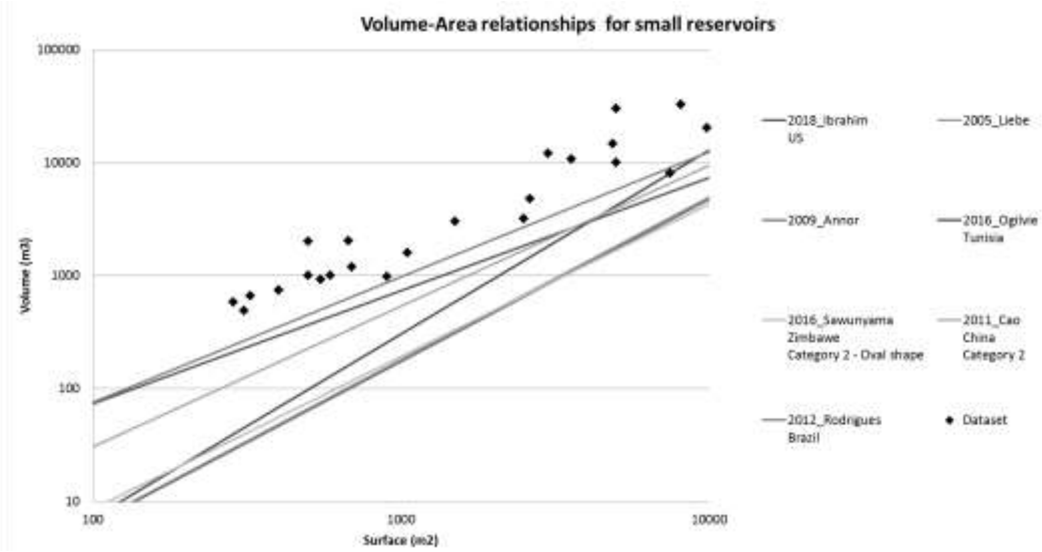


Figure 7. Comparison of volume-area relationships with dataset values

Alternatively, the volume of farm ponds is often estimated by also adding the height and slope variables and assuming a regular geometric shape. Following the example of Ouyang et al. (2017), a trapezoidal shape is assumed and, for sake of simplicity, an inverted truncated pyramid with square surfaces (see **Figure 8**).

$$V_{NBS\,C} = f(h, A, \alpha, \phi, V_{silt})$$

$$A_{bottom} = \phi\left(\sqrt{A_{top}} - 2\frac{h - h_{sed}}{\tan\alpha}\right)^2$$

$$V_{NBS} = \frac{\left(A_{top} + A_{bottom} + \sqrt{A_{top} \cdot A_{bottom}}\right) \cdot (h - h_{sed})}{3}$$

Where:

- h height
- h_{sed} height of the accumulated sediment
- A_{top} top surface area
- A_{bottom} bottom area
- α side slope
- ϕ NBS porosity
- V_{silt} lost volume due to siltation

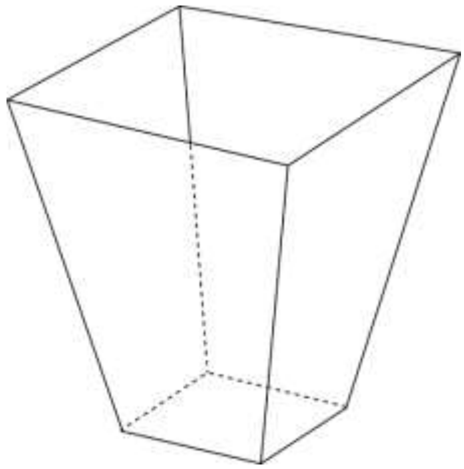


Figure 8. Simplified shape of the farm pond

The goodness of the estimate of the farm pond volume is reported in **Table 31**, comparing the most suitable relationships from literature with the volumes estimated assuming the regular truncated pyramidal shape with different side slopes; the heights of accumulated sediment are neglected in this phase. As visible, all the literature relationships underestimate the volume calculated from the area. The best assumption is that of a farm pond with a slope of 1:1, in agreement with some literature cases (Alvarez et al 2008; Ueno et al., 2019). Smoother slopes (1:3, 1:5), instead, lead to errors comparable to literature relationships. This confirms that farm ponds are usually optimised to store as much runoff as possible, with less attention to other NBS benefits suitable for shallower slopes (e.g. biodiversity).

Table 31. Percentage errors of different volume-area relationships

	V(A) 2018 Ibrahim	**V(A) 2009 Annor**	**V(A) 2012 Rodrigues**	**V(A) 2008 Roost**	**V(A, α) Trunc. Pyr. 1:1**	**V(A, α) Trunc. Pyr. 1:3**	**V(A, α) Trunc. Pyr. 1:5**
Mean	-53%	-87%	-39%	-47%	10%	-21%	-28%
Standard dev.	30%	9%	30%	35%	34%	29%	36%
Min	-82%	-95%	-73%	-79%	-41%	-56%	-71%
Percentile 0.25	-64%	-93%	-58%	-59%	-20%	-40%	-54%
Percentile 0.50 (Median)	-60%	-90%	-46%	-55%	2%	-31%	-45%
Percentile 0.75	-53%	-85%	-34%	-49%	24%	-2%	-8%
Max	37%	-61%	36%	56%	78%	50%	42%
n° samples	24	24	24	23	22	22	22

On the basis of literature and of the dataset values, the average design parameters for each NBS C category were chosen and are summarised in **Table 32**. Below are the assumptions made to select the chosen values:

— The literature on managed aquifer recharge (MAR) resulted less rich, with few applications of ponds on the scale of our interest (e.g. Teatini et al., 2015). However, in accordance with the approaches used to identify suitable areas for NBS for rainwater harvesting in agricultural areas done by Singh et al. (2017) and Kumar et al. (2017), farm pond areas can also be suitable to become an infiltration pond, if the infiltration characteristics of the area are suitable. Therefore, infiltration ponds of the same size as farm ponds were assumed.

- The height of shallow storage ponds was chosen equal to the median value obtained from the dataset of farm ponds, i.e. 2.5 m.
- The height of deep storage ponds was chosen in accordance with the highest value registered in the farm ponds dataset (75^{th} percentile, 3.4 m – maximum value, 8.1 m), and is assumed equal to 5 m.
- The height of the infiltration pond was assumed to be lower in comparison to farm ponds to limit the compaction of the bottom surface (Bouwer 2002; Jódar-Abellán et al., 2017), assumed equal to 1 m.
- The wetland for pre-treatment was assumed to be a free water surface (FWS) system; FWS used for event-driven stormwater runoff are usually designed with alternating deep and shallow areas varying from 0.2 to 1.0 m (Kadlec and Wallace, 2009); a typical value of 0.8 m is assumed, to consider a deeper area to enhance the sedimentation capacity.
- It was assumed that there are no plants within the ponds.
- The apparent porosity of the wetland was assumed equal to 0.8 to consider the plants volume, in agreement with literature values for FWS systems (Crites et al., 2006).
- The apparent porosity of the trees was assumed equal to 0.9 to consider the plants volume
- The slopes of the ponds were assumed in accordance with those that best fit the dataset of farm ponds, i.e. 1:1.
- In order to better support biodiversity, slopes of pre-treatment wetlands were assumed to be gentler in comparison to ponds, i.e. 1:3.
- The infiltration wooded areas were considered a more naturalistic area with very gentle slopes, assumed equal to 1:5.
- No siltation effect was considered, neither for NBS with pre-treatment stage nor for NBS with single pond and high infiltration rate (C2.1).
- The siltation effect was assumed considering an average growth of sediment height per the number of years considered. A dedicated dataset was developed by reviewing the available literature to estimate the siltation characteristics of farm ponds (see Attachment 5). The results are summarised in **Table 33**.

Table 32. Dimensional parameters chosen for each NBS category

NBS C category	Description	Height – h (m)	Side slope – α (°)	NBS porosity ϕ (-)	Siltation
C1.1.1	Storage pond (shallow)	2.5	45° (1:1)	1	yes
C1.1.2	Storage pond (deep)	5	45° (1:1)	1	yes
C1.2.1	Pre-treatment pond	1	negligible	1	-
	Storage pond (shallow)	2.5	45° (1:1)	1	no
C1.2.2	Pre-treatment pond	1	negligible	1	-
	Storage pond (deep)	5	45° (1:1)	1	no
C1.3.1	Pre-treatment wetland	0.5	negligible	0.8	-
	Storage pond (shallow)	2.5	45° (1:1)	1	no
C1.3.2	Pre-treatment wetland	0.5	negligible	0.8	-
	Storage pond (deep)	5	45° (1:1)	1	no
C2.1.1	Infiltration Pond (high infiltration)	1	45° (1:1)	1	no
C2.1.2	Infiltration Pond (low infiltration)	1	45° (1:1)	1	yes
C2.2	Pre-treatment pond	1	negligible	1	-
	Infiltration pond (high infiltration)	1	45° (1:1)	1	no
C2.3	Pre-treatment wetland	0.5	negligible	0.8	-

NBS C category	Description	Height – h (m)	Side slope – α (°)	NBS porosity ϕ (-)	Siltation
	Infiltration pond (high infiltration)	1	45° (1:1)	1	no
C2.4	Infiltration wooded area	1	11° (1:5)	0.9	yes

Table 33. Statistical analysis of physical and dimensional parameters regarding sediment trapping of farm ponds. Data from : Ambati et al. (2011), Brainard and Fairchild (2012), and Verstraeten and Poesen (2002).

	Storage volume loss (%/year)	h sed (cm/y)	dry bulk density sediment (t/m3)	Trapping efficiency (%)
Mean	0.71%	1.39	1.13	59%
Standard dev.	0.54%	0.50	0.17	19%
Min	0.03%	0.72	0.78	10%
Percentile 0.25	0.28%	1.03	0.95	54%
Percentile 0.50 (Median)	0.60%	1.52	1.13	62%
Percentile 0.75	1.03%	1.67	1.29	68%
Max	1.77%	2.07	1.35	100%
n° samples	16	7	21	21

2.1.3.3 Runoff

In accordance with several works related to suitability maps for rainwater harvesting (e.g., De Winnaar et al., 2007; Ramakrishnan et al., 2009; Kadam et al., 2012; Jha et al., 2014; Napoli et al., 2014; Buraihi and Shariff, 2015; Mahmoud and Tang, 2015; Nagarahan et al., 2015; Rejani et al., 2017; Kumar et al., 2017; Singh et al., 2017; Singhai et al., 2019), the SCS-CN method was used to estimate runoff from areas without NBS ($A_{NO\ NBS}$). The SCS-CN can be seen as a simple large scale *"proxy"*, such as the one of interest for the study, to correlate the potential runoff of an area to its landscape and climate features. Interestingly, the SCS-CN was also used as a method to identify suitable sites for either accumulation (NBS C1) or infiltration (NBS C2) of harvested rainwater by both Kumar et al. (2017) and Singhai et al. (2019), confirming the suitability of the SCS-CN method for the aim of the study.

Following the simplification assumed by Kumar et al. (2017) and the results of Napoli et al. (2014), the runoff depth (Q), in mm/event, is calculated as follows

$Q = \frac{(P - 0.2\,S)^2}{(P + 0.8\,S)}$	$P > 0.2\,S$
$Q = 0$	$P \leq 0.2\,S$

Where

— P rainfall depth, in mm/event

— S retention value, in mm/event

The retention value,S, represents the maximum potential retention before the runoff begins, and is calculated as follows

$$S = \frac{25400}{CN} - 254$$

Where CN, the curve number, is a dimensionless run-off index function of landscape features, i.e. hydrological soil group and land use. The indications on CN values in function of land use and hydrological conditions are reported in Kumar et al. (2017).

Alternatively, FAO guidelines for rainwater harvesting in agricultural areas propose the following simplified approach to estimate annual runoff as follows

$$Q = runoff\ coefficient \cdot P_y$$

where P_y is the annual precipitation (mm/year) and the runoff coefficient is selected according to land use and annual precipitation as follows

Table 34. Runoff coeffients function of land use and annual precipidation. FAO (2014)

Land use	**Runoff coefficients**		
	$P_y = 200–500$ **mm/y**	$P_y = 500–1000$ **mm/y**	$P_y = 1000–1500$ **mm/y**
Concrete	0.75–0.85	0.75–0.90	0.80–0.90
Cement tile	0.65–0.80	0.70–0.85	0.80–0.90
Clay tile (machine-made)	0.40–0.55	0.45–0.60	0.50–0.65
Clay tile (handmade)	0.30–0.40	0.35–0.45	0.45–0.60
Masonry in good condition	0.70–0.80	0.70–0.85	0.75–0.85
Asphalt paved road in good condition	0.70–0.80	0.70–0.85	0.75–0.85
Dirt road, courtyard	0.15–0.30	0.25–0.40	0.35–0.55
Cement soil	0.40–0.55	0.45–0.60	0.50–0.65
Bare plastic film	0.85–0.92	0.85–0.92	0.85–0.92
Plastic film covered with sand/soil	0.30–0.50	0.35–0.55	0.40–0.60
Natural slope (rare vegetation)	0.08–0.15	0.15–0.30	0.30–0.50
Natural slope (rice vegetation)	0.06–0.15	0.15–0.25	0.25–0.45

Once the runoff depth is known, the runoff volume R entering in the NBS is calculated as

$$R = Q\ A_{NO\ NBS}$$

2.1.3.4 Infiltration

Infiltration affects both storage NBS (C1), as loss, and infiltration NBS (C2), as potential capacity to recharge the aquifer. Therefore, two different simplified approaches were considered for the two different groups of NBS.

For **MAR systems (NBS C1)** the hydraulic loading rate (HLR) concept, i.e. the long-term average infiltration capacity, was used to evaluate infiltration, rather than the conventional infiltration rate estimations, such as Darcy's law (Bouwer 2002; Jódar-Abellán et al., 2017; Maliva 2019). Indeed, the HLR accounts for seasonal variability in dry and wet periods as well as changes in infiltration rate conditions throughout the year. For sake of simplicity, fixed values of HLRs were assumed in function of soil texture and are summarised in **Table 36**, in which the HLRs are also compared with the saturated hydraulic conductivities estimated by the recent work of García-Gutiérrez et al. (2018). Firstly, the median value of saturated hydraulic conductivities from García-Gutiérrez et al. (2018) agrees well with typical ranges reported in literature for infiltration coefficients (Bettes 1996). Secondly, Bouwer (2002) provides the HLR only for coarse textured soils, considered suitable for MAR systems. The soil textures indicated by Bouwer (2002) are in agreement with the infiltration rate threshold assumed in studies regarding suitability maps for MAR system, with the minimum value equal to 25 cm/d as reviewed by Sallwey et al., (2019). Assuming an equal threshold value in developing the favourability map of NBS C2, the infiltration rate capacity is calculated as a function of the HLR as follows

$$I_{NBS\ C2} = \frac{A_{NBS}\ HLR}{F_c}$$

Where:

— HLR[9] is function of the soil texture and is equal to
  - **30 m/y**, sandy loam
  - **100 m/y**, loamy sand and silt
  - **300 m/y**, sand

— F_c is a dimensionless clogging factor

Infiltration rates in MAR systems are affected by clogging, which can be due to physical, chemical and biological processes (Bouwer 2002; Jódar-Abellán et al., 2017; Maliva 2019). However, proper pre-treatment stages (C2.3 and C2.4) or maintenance activities (C2.1) are considered to be able to recover the design infiltration capacity. On the other hand, some NBS C2 here considered assume a more naturalistic environment, with unmanaged clogging (C2.2 and C2.5), in order to promote other NBS side-benefits, such as biodiversity. Unfortunately, the reduction of the infiltration rate due to clogging in full scale surface infiltration systems has been scarcely reported in literature (Maliva 2019). Therefore, a simplified approach was needed to account for the clogging effect, assuming the clogging factors (see **Table 35**) in agreement with the safety factors proposed by (Bettes 1996) for infiltration system design.

Table 35. Clogging factors assumed for the different MAR NBS, by Bettes (1996)

NBS C category	Description	Clogging factor, F_c
C2.1.1	Infiltration Pond (high infiltration)	1
C2.1.2	Infiltration Pond (low infiltration)	10
C2.2	Pre-treatment pond + Infiltration pond (high infiltration)	1
C2.3	Pre-treatment wetland + Infiltration pond (high infiltration)	1
C2.4	Infiltration wooded area	10

Table 36. Comparison of hydraulic loading rates (HLRs) of MAR systems with saturated hydraulic conductivities from literature, function of soil texture. Values in red are those lacking in the original reference and assumed for this study. Green cells show soil textures with a median saturated hydrulic

[9] HLR for other soil textures are not defined, since other soil textures are excluded because they were considered unsuitable for MAR systems during the favourability map development (constraint maps)

conductivity higher than the constrain value for suitability of MAR systems (25 cm/d – Sallwey et al., 2019), while red cells indicate soil texture with lower values.

	Bower (2002) HLR (m/y)		**Garcia-Gutierrez et al. (2018)* Sat. hydr. cond. (median)**			**Bettes (1996) Infiltr. Coeff.**	
	min	**max**	**(cm/h)**	**(cm/d)**	**(m/s)**	**(m/s) min**	**(m/s) max**
clay			0.16	3.84	4.44E-07		3.00E-08
clay loam			0.22	5.28	6.11E-07		
silty clay			0.25	6.00	6.94E-07		
silty clay loam			0.34	8.16	9.44E-07	1.00E-08	1.00E-06
sandy clay			0.41	9.84	1.14E-06		
sandy clay loam			0.5	12.00	1.39E-06	1.00E-10	1.00E-07
loam			0.72	17.28	2.00E-06	1.00E-07	5.00E-06
silt loam			0.69	16.56	1.92E-06	1.00E-07	1.00E-05
sandy loam	30		1.1	26.40	3.06E-06	1.00E-07	1.00E-05
loamy sand	100		5	120.00	1.39E-05	1.00E-04	3.00E-05
silt	100		5.21	125.04	1.45E-05		
sand	300	500	23.95	574.80	6.65E-05	1.00E-05	5.00E-05

* Among the 19121 soils considered in the study

Storage NBS (C1) are commonly waterproofed in developed countries, avoiding infiltration. However, if the NBS is implemented in an area with poor infiltration capacity, typically with a high percentage of clay, waterproofing can be done by compacting the clay itself. Therefore, the infiltration rate of storage NBS is assumed as follows

$$I_{NBS\,C1} = A_{NBS}\, q$$

Where q[10] is the infiltration rate, which is estimated in function of soil texture and equal to **1.0 x 10^{-9} m/s**, for clay soil texture, value from monitored seepage of a wetland waterproofed with compacted clay (Kadlec and Wallace, 2009).

2.1.3.5 Evaporation and Evapotranspiration

Evaporation and evapotranspiration are calculated as a function of potential evapotranspiration, ET_0 and a correction coefficient, which can be a crop coefficient for vegetated NBS or an evaporation coefficient for non-vegetated NBS. This is a common approach used to estimate losses due to evaporation and evapotranspiration, as also done by Wisser et al. (2010) in the estimation of farm ponds on a worldwide scale. The evapotranspiration losses of NBS are calculated as follows

$$ET_{NBS} = A_{NBS}\, k_p\, ET_0$$

Where k_p is the dimensionless evapotranspiration loss coefficient. Although the climatic and seasonal variability of k_p is well-known, especially for constructed wetlands and willow systems (e.g., Kadlec and Wallace, 2009; Papaevangelou et al., 2012; Frédette et al., 2019)[11], it was preferred, for sake of simplicity, to neglect this variability, since climatic and seasonal variability in evapotranspiration rates is already well represented by ET_0. Therefore, constant annual average values are assumed for k_p, varying them only in function of the NBS type:

— **0.6** (evaporation only) for ponds (Wisser et al., 2010)

— **1.5** (evapotranspiration) for surface flow wetlands (Kadlec and Wallace, 2009)

— **2.5** (evapotranspiration) for wooded areas (Frédette et al., 2019)

[10] q for other soil textures are not defined, since NBS for storage implemented on other soil textures are assumed to be waterproofed with plastic liners

[11] Higher average values of k_p are commonly reported for Mediterranean countries that are warmer than temperate ones, and in summer seasons.

2.1.3.6 *Simplified water budget: definition of droughts and flood mitigation performance*

A simplified water budget was defined for each categorised NBS, on the basis of simplified assumptions used to estimate the following NBS droughts performance:

— Storage NBS (C1): volume available for emergency irrigation during drought periods

— Infiltration NBS (C2): annual infiltrated volume of intercepted runoff

The water budget of **storage NBS (C1)** was solved assuming that:

— The drought period lasts 1 month, i.e. considering neither runoff nor precipitation during the month, but only evaporation losses

— The typical NBS to catchment watershed ratio of farm ponds allows for a full NBS storage volume before the beginning of the drought period, i.e. the runoff from the months preceding the drought period are sufficient to fill the NBS storage volume, which is small in comparison to the annual precipitation falling onto the harvested catchment. The NBS storage volume is used for emergency irrigation in the event of severe drought events in the summer. This assumption is in agreement with the role of farm ponds in developed countries (e.g., Wisser et al., 2010; Alvarez et al., 2009)

Consequently, the drought mitigation performance indicator of NBS C1, i.e. the volume available for emergency irrigation during drought periods, is calculated as follows,

$$V_{drought,NBS\ C1} = V_{storage,pond} - \max[ET_{NBS,storage\ pond,m}] - I_{NBS\ C1,m}$$

Where:

— $V_{storage,pond}$ is the volume of the storage pond, calculated with the methodology provided in section 2.1.3.2; pre-treatment volumes (NBS C1.2 and C1.3) are neglected

— $ET_{NBS,storage\ pond,m}$ is the monthly evaporation/evapotranspiration calculated with the methodology provided in section 2.1.3.5; the maximum monthly evaporation/evapotranspiration is assumed, leading to solve the simplified water budget in the most stressful condition expected for the NBS

— $I_{NBS\ C1,m}$ is the water lost by infiltration in a month; this value is considered only for non-waterproofed storage ponds

The water budget for **infiltration NBS (C2)** was based on the following assumptions:

— Infiltration NBS receives the runoff from the grid area A_{NBS} all year round, assuming that the height of the infiltration basin is suitable to buffer most of the runoff generated per rain event

— Precipitation and evaporation/evapotranspiration are not considered, since they can be considered negligible in comparison to the infiltration capacity of the NBS. This assumption is considered valid, since infiltration NBS are constrained to soils with high infiltration rates

— The NBS infiltrate all the intercepted runoff in function of the annual hydraulic loading rate, independently from the available NBS volume. This assumption considers that the hydraulic loading rate of the MAR system already accounts for the inability to infiltrate all the generated runoff, on an annual scale, due to the stochastic variability of rain events, in terms of both intensity and frequency

Therefore, the drought mitigation performance indicator of NBS C2, i.e. the annual infiltrated volume of intercepted runoff, is calculated as follows,

$$R_y \geq I_{NBS\ C2,y} \qquad V_{drought,NBS\ C2} = I_{NBS\ C2,y}$$

$$R_y < I_{NBS\ C2,y} \qquad V_{drought,NBS\ C2} = R_y$$

Where:

— R_y is the annual runoff of $A_{NO\ NBS}$, calculated with the methodology provided in section 2.1.3.3

— $I_{NBS\ C2,y}$ is the annual infiltration capacity of the infiltration NBS, calculated with the methodology provided in section 2.1.3.4

2.1.3.7 Summary of the features of the proposed simplified approach

A simplified approach was proposed, based on the categorisation of NBS C and on expert-based assumptions. The methodologies selected to calculate the different items necessary for the resolution of the water budget allow to properly account for landscape, climate and design variables (**Table 37**), permitting an easy extrapolation on a European scale for the construction of favourability and opportunity maps. The categorisation of NBS C also made it possible to solve simplified water budgets to estimate the NBS performance, considering a limited number of water budget items for different NBS, as summarised in **Table 38**.

Table 37. Water budget items and considered variables

	Variables and methods	**Lands.**	**Clim.**	**Design**	**References**
V	Trapezoidal shape Area NBS Slope Height Vegetation volume Siltation			x	Alvarez et al. (2008); Ouyang et al. (2017); Ueno et al. (2019); Bouwer (2002); Jódar-Abellán et al., (2017); Verstraeten and Poesen (2002)
R	SCS-CN method Area no NBS Precipitation Soil type Soil use	x	x		Singhai et al., 2019; Singh et al., 2017; Kumar et al., 2017; Rejani et al., 2017; Nagarahan et al., 2015 and others
P	Monthly precipitation Area NBS		x	x	
ET	Monthly reference evapotranspiration Area NBS Vegetation		x	x	Wisser et al. (2010) Kadlec and Wallace (2009) Frédette et al. (2019)
I	Area NBS Soil texture Clogging	x		x	Bouwer (2002) Bettes (1996)

V = volume; R = runoff; P = precipitation; ET = evapotranspiration; I = infiltration

Table 38. Items of the water budget considered for each NBS category

NBS C category	Description	V	R	P	ET	I
NBS C1 – Storage						
C1.1.1	Storage pond (shallow)	x			x	x
C1.1.2	Storage pond (deep)	x			x	x
C1.2.1	Pre-treatment pond			neglected		
	Storage pond (shallow)	x			x	x
C1.2.2	Pre-treatment pond			neglected		
	Storage pond (deep)	x			x	x
C1.3.1	Pre-treatment wetland			neglected		
	Storage pond (shallow)	x			x	x
C1.3.2	Pre-treatment wetland			neglected		
	Storage pond (deep)	x			x	x
NBS C2 – Infiltration (MAR)						
C2.1	Infiltration Pond (high infiltration)		x			x
C2.2	Infiltration Pond (low infiltration)		x			x
C2.3	Pre-treatment pond			neglected		
	Infiltration pond (high infiltration)		x			x
C2.4	Pre-treatment wetland			neglected		
	Infiltration pond (high infiltration)		x			x
C2.5	Infiltration wooded area		x			x

V = volume; R = runoff; P = precipitation; ET = evapotranspiration; I = infiltration

2.1.4 Side benefits

2.1.4.1 Water quality for NBS C

The following side benefits in terms of water quality performance were considered for NBS C:

— TSS removal, assumed for all the NBS according to median trapping efficiency from literature review (**Table 33**);

— total nitrogen, total phosphorous, and pesticide removal, assumed only for NBS C including a wetland as pre-treatment (i.e. NBS C1.3 and NBS C2.3) and estimated with the same methodology described for NBS B (section 2.1.1 for TN and TP, section 2.1.2 for pesticides).

2.1.4.2 Flood control

The capacity of sparse NBS (e.g. the so-called geographically isolated wetlands) to contribute to reduce flood risk, has been a matter of discussion within the Scientific community. A number of recent works (e.g. Salazar et al., 2012; Acreman and Holden, 2013; Lane et al., 2018) have actually helped to clarify the role of NBS on this side benefit. Substantially, it is true that wetlands or buffer strips, if properly designed (see Gumiero and Boz, 2017 and Zak et al., 2019 as examples for buffer strips), are capable of providing significant additional retention volumes. However, the additional volume provided is only significant for frequent rain events (maximum return time 2-5 years), and of little relevance for extreme events (return time >30 years) usually subject to flood protection policies[12]. This does not mean that NBS designed for flood protection cannot be multipurpose: for instance, big retention basins for flood protection can include a wetland for nutrient removal from the low river flow. However, this is not the scale and the target of the NBS here proposed; since they aim at intercepting diffuse pollution or runoff within the catchment, NBS must be as much widespread as possible. Accordingly, the NBS here proposed can give some interesting benefits to farmers in terms of flood risk, reducing the

[12] For instance, the EU Floods Directive 2007/60/EC requires the identification of flood hazard maps for three scenarios: P1, low probability; P2, medium probability; P3, high probability. The most frequent flood scenario is commonly identified with a return time equal to 30 years in Italy, which is out of the efficacy range for the NBS targeted by this study.

disadvantages driven by rain events with short return times; for this reason, the flood risk reduction benefit is not excluded from the proposed analysis.

On the basis of the previous consideration, a “proxy” indicator was proposed to estimate the effects of NBS in terms of flood risk reduction. This proxy was the additional storage volume available thanks to the NBS, following a simplified approach: during high flow the water level throughout the NBS can rise by an additional height intended only for flood protection (i.e. not usable for drought mitigation purposes, for instance). This assumption is in agreement with the proposed approach to estimate the side benefit of flood mitigation at catchment scale for the analysed case studies (e.g. Feasibility Study “Nature-based solutions for climate change adaptation and water pollution in agricultural regions”, Lot 5: LDP in a continental environment). Therefore, the retaining volume for flood side benefit is calculated as follows

$$V_{flood} = A_{NBS} \cdot h_{flood}$$

Where h_{flood} is the additional height for flood mitigation, for sake of simplicity, equal to 1 m for the considered NBS C, as well as for wetlands and integrated buffer strips for diffuse pollution. Contrarily, the flood benefit is neglected for all the NBS in which an additional volume is usually not considered, i.e. VDDs, buffer strips, and NBS A.

The <u>flood mitigation performance for low intensity rain events</u> is estimated considering the NBS capacity to store, as a “proxy”, the runoff developed by a rain event with return time equal to 1 year, as follows

$$\eta_{flood} = \frac{V_{flood}}{R_{P,return\ time\ 1\ year}}$$

Where:

— η_{flood} is the flood mitigation efficiency (in %) for low intensity rain events

— $R_{P,return\ time\ 1\ year}$ is the runoff volume at pixel level, calculated with the method presented in section 2.1.3.3, considering as precipitation the average of the maximum daily rainfall heights

2.1.4.3 Biodiversity support

2.1.4.3.1 Habitat definition

For what concerns **biodiversity**, the benefits of newly created NBS in intensive agriculture landscapes are well known (Gibbs 2000, Herzon and Helenius 2008; Ma 2008, González et al. 2016; McCracken et al 2012; Strand and Weisner 2013, Stutter et al. 2019). The recently published European Commission report (European Commission 2020a) states that – regarding NBS for agriculture – *“there was little evidence on agrobiodiversity and the link to NBS (such as agro-ecological practices) in the reviewed research projects, but several LIFE projects made a significant contribution to increase biodiversity in (intensively) used farmland. This included restoring such farmland to valuable semi-natural habitats, agrienvironmental measures to restore feeding and resting areas for specific bird species, biodiversity-friendly agricultural practices, or measures to reduce the impact of intensive agriculture on nearby nature areas”*.

More in detail, the different NBS considered in the present study correspond to different habitat types (see the following table) showing different performance in providing the ecosystem service of “supporting biodiversity”.

Table 39. Summary of habitat type for each NBS

NBS	Category	Habitat type
Treatment Ponds	A	Not significant
Subsurface CW	A	Reed (or other emergent macrophite) patches; no aquatic habitat
Free water CW	A-B	Wetland
Vegetated Ditches	B	Wetland

NBS	Category	Habitat type
Wooded Buffer Strips	B	Patches/strips of Wooded habitat
Herbaceous Buffer Strips	B	Not significant
Integrated buffer strips	B	Wetland
Farm (storage) ponds	C	Pond
Storage Wetlands/marshes	C	Wetland
Infiltration Ponds	C	Pond
Infiltration Wetlands/marshes	C	Wetland
Infiltration wood	C	Patches/strips of Wooded habitat

Of the two "families" of NBS A considered (**wetlands** and **ponds**) only wetlands may provide some significant effect in terms of biodiversity support. The chemical conditions of treatment ponds do not allow colonization by plants or animals, with the exception of a few very tolerant organisms, not interesting for wildlife conservation.

Moving to wetlands, subsurface systems (or reed beds, i.e. patches of *Phragmites australis*) could contribute to the landscape diversification and are an interesting habitat for many bird species (Gilbert et al. 2005; Benassi et al.2009), but the lack of an aquatic habitat to be colonized by aquatic fauna and flora provides minor benefits compared to free water wetlands.

The availability of free water **Wetland** habitats is of great importance (the most important among the habitats created by the NBS of the present study) since about two-thirds of the European wetlands that existed 100 years ago have been lost (https://www.eea.europa.eu/publications/92-9167-205-X/page015.html). Moreover, several studies show the ability of restored wetlands to contribute to the conservation of rare and endangered species (Gibbs 2000; Strand & Weisner 2013).

The habitat of **Vegetated ditches** is **wetland**-like but of limited extension. Its importance for several groups of plants and animals is well known (Rolke et al. 2018; Teurlincx et al. 2018; Herzon and Helenius 2008), even though their small size does not allow for all the ecological functions provided by larger wetlands.

Wooded buffer strips could support biodiversity in intensive agriculture landscapes by providing **wooded habitats** hosting several species of insects, reptiles, birds and small mammals (Stutter et al. 2019; Hietala-Koivu 2004) while the vegetation of BS in intensive agriculture areas is "dominated by grasses and ruderal species" (Ma 2008), showing little interest for plant biodiversity. BS' ability to support biodiversity, however, depends on the management practice (Hille et al 2018) and the benefit for rare or endangered species is nearly negligible, not comparable to that provided by NBS restoring aquatic habitats.

The habitat opportunities offered by **Herbaceous buffer strips** to endangered species are very poor and emerge only in case of BS larger than 5 metres (Hille et al 2018; McCracken et al 2012). It is therefore reasonable to consider the benefit of herbaceous BS as negligible in terms of support to biodiversity.

The contribution of **farm ponds** in supporting biodiversity has been studied in southern Europe, highlighting a significant effect even if not comparable to free water CWs. The homogeneous and non-vegetated shore of farm ponds, in conjunction with their intensive management and the high water level variability sharply reduce the ability of farm ponds to support biodiversity (Gallego et al 2015; Ferreira and Beja 2013). The presence of natural-like wetlands upstream the pond – often used to reduce the sediment load and treat the inflow water – would obviously increase the capacity of the whole system to support biodiversity, thanks to the availability of a **wetland habitat**. Analogously, storage wetlands/marshes (category C) support biodiversity as treatment wetlands (categories A-B).

No specific studies are available on the ability to support biodiversity of *Managed Aquifer Recharge* (MAR) techniques, however **infiltration ponds** and **infiltration wetlands** could be assimilated, in terms of habitat provided, to other kinds of ponds and wetlands. The creation of **infiltration woods** as a MAR technique is quite new and still rarely practised. The habitat provided by this solution is a patch of wet forest periodically submerged, mainly during the winter season (from October to March). In the absence of studies on the effects of these systems on biodiversity, but considering that this solution creates isolated patches of **wooded habitat**, its capacity to support biodiversity could be assimilated to that of **wooded buffer strips**.

Thus, to assess the potential "biodiversity support" benefits of the mentioned NBS the "capacity to support biodiversity" for each of the habitat types created by the NBS must be quantified:

— Wetlands

— Patches/strips of Wooded habitat

— Reed patches without aquatic habitat

— Ponds

Among the 4 different habitat types, considering the landscape where the NBS are expected to be created, wetlands are the most interesting habitat type, for their intrinsic capacity to host rare and endangered species. The benefits provided by other habitat types will be less than those provided by wetlands, and consequently their capacity to support biodiversity were estimated as a fraction of the maximum benefit provided by the best performing wetland habitat.

2.1.4.3.2 Wetlands

Constraints: existence of a "demand" of the new ecosystem for "biodiversity support"

Wetlands provide the ecosystem service of supporting biodiversity in any kind of agricultural landscape, regardless of crop type. The importance of the ecosystem service drastically decreases only in the case of landscapes already rich in wetlands: thus the benefit could be considered negligible if in the unit area the *Corine Land Cover* (CLC) class 4.1 (inland wetland) covers more than 50% of the area.

Quantification

According to Gibbs (2000) and Strand and Weisner (2013), the capacity of wetlands to provide *habitat for insects, reptiles and amphibians* does not depend on their size; any wetland, even the smallest, can contribute to provide habitats for plants, insects, amphibians and reptiles. Among these taxonomic groups there is no evidence that species richness increases with wetland size, even though, obviously, the larger the wetland, the bigger the available habitat.

To ease of *colonization by reptiles and amphibians*, however, according to Gibbs (2000) the newly created wetland must be located less than 500 metres from an existing water body. Wetlands for diffuse pollution control (category B) are generally located along or beside existing water courses, but wetlands for manure treatment (category A, e.g. a final FWS polishing stage) and those of category C may not. Thus, a possible difference between the two conditions should be considered.

Moving to the role of wetlands in providing *habitat for birds*, Strand and Wisser (2013) – based on the results of the analysis done on 24 wetlands in Sweden – notes that "*the maximum number of bird breeding species in the 24 wetlands showed positive relations with wetland size* [size of the wetlands ranges between 0.25 and 6.1 hectares] *but for wetlands smaller than 2 hectares no relation could be seen*". Hence, species richness appears to increase with the size of the wetland, for wetlands larger than 2 hectares.

Based on such considerations, the capacity of wetlands to support biodiversity can be quantified by a dimensionless value per m^2 consisting of 3 factors:

A. The ability to provide *habitat for plants, insects, amphibians and reptiles*, which depends linearly on the surface of the wetland;

B. The ease of *colonization of the habitat by amphibians and reptiles*, which occurs only when the wetland margin is located at less than 500m away from an existing water body, and depends linearly on the surface of the wetland and is added to factor A;

C. The ability to provide *habitat for birds*, which occurs only when the wetland is larger than 2 hectares, and depends linearly on the surface of the wetland and is added to factors A and B.

2.1.4.3.3 Patches/strips of wooded habitat

Constraints: existence of a "demand" of the new ecosystem for "biodiversity support"

The biodiversity support operated by this kind of newly created habitat could be considered negligible in already diverse landscapes, for the presence of a mosaic of cultivated and natural areas, as is the case of the following 3 CLC classes:

2.4.2 Complex cultivation patterns

2.4.3 Land mainly occupied by agriculture, with significant areas of natural vegetation

2.4.4 Agro-forestry areas

Therefore, the benefit could be considered negligible if in the unit area the 3 CLC classes above cover more than 50% of the pixel.

Quantification

For the considerations reported above, the benefit for biodiversity of Strips or patches of wooded habitat could be estimated as 30% of the maximum benefit provided by a large wetland. Therefore, the benefit could be quantified as 0.30 of biodiversity value (variable from 0 to 1) per m^2.

2.1.4.3.4 Reed Patches

Constraints: existence of a "demand" of the new ecosystem for "biodiversity support"

There is no specific constraint for this type of habitat. It can deliver biodiversity support services in any area of interest of the present study.

Quantification

Reed bed habitat (also known as *Phragmition*) is listed in the annex I of the habitat of European interest (even though not considered a "priority" habitat). Therefore, it is a valuable habitat hosting several species of rare and endangered bird species but, according to Benassi et al (2009) patches sized less than 10.000 m^2 are too small to host breeding couples of marshland specialists such as, *Ixobrychus minutus, Acrocephalus scirpaceus* and *Acrocephalus arundinaceus.* To fully support rarer and endangered species, the newly created habitat should have "a size greater than 10 ha with a patchy mosaic of reed beds, open waters, and other edge features", a condition typical of FWS wetlands.

Considering that this habitat type is referred to NBS A (subsurface flow manure treatment wetlands) it can be assumed that most of the time the location of the NBS would not allow to fully deliver its potential ecological service to support biodiversity and certainly the best conditions mentioned above for the FWS wetlands would not occur. However, systems larger than 10.000 m^2 could certainly provide an interesting habitat for birds.

The benefit for reed bed could be considered negligible for NBS smaller than 10.000 m^2 and – for system larger than that – it could be estimated as 20% of the maximum benefit provided by a large wetland. Therefore, the benefit could be quantified as 0.20 of thebiodiversity value (variable from 0 to 1) per m^2.

2.1.4.3.5 Ponds

Constraints: existence of a "demand" of the new ecosystem for "biodiversity support"

As for the wetlands.

Quantification

For the consideration reported above, the benefit for biodiversity of the pond habitat could be estimated as 30% of the maximum benefit provided by a large wetland. Therefore, the benefit could be quantified as 0.30 of the biodiversity value (variable from 0 to 1) per m^2.

2.1.4.4 Biomass-driven benefits

A number of side-benefits of the proposed NBS are linked to the provision of ecosystem services related to the production of biomass. Therefore, biomass-driven benefits discussed here are assumed null for pond NBS.

2.1.4.4.1 Biomass estimation for NBS

Among the set of proposed NBS, two different types of biomass can be identified:

- Aquatic plants in wetlands (NBS A, NBS B1, pre-treatment in NBS C1.3 and C2.3) and vegetated drainage ditches (NBS B2)
- Trees in buffer strips (NBS B3) and wooded infiltration areas (NBS C2.4)

For sake of simplicity, the two types of biomass are estimated, as "proxies", on the basis of the following assumptions (see **Table 40**):

- Two typical plant species for each of the two types of biomass were selected and averaged to obtain a mean value for each type according to literature evidence
- Despite the higher biomass production (Avellán and Gremillion, 2019), both *A. donax* and *C. papyrus* were neglected, the former because it is considered a dangerous weed across whole Europe and the latter because it is a typical plant of tropical climates
- Two species typically used in riparian buffer strips were selected as representative of wood biomass, among the many available for short rotation forestry (Christen and Dalgaard, 2013)
- Only above-ground biomass in terms of dry weight (d.w.) is considered
- Floating and submerged plants in FWS wetland are neglected, i.e. only biomass from emergent plants is considered for wetlands

Table 40. Above-ground biomass values for different types of plants

Type of plant	**Species**	**Age of max. biomass growth** (years)	**Above-ground biomass production at max. growth** ($g_{d.w.}/m^2$)	**HHV**** ($MJ/kg_{d.w.}$)	**Ash**** (%)
Wetland plants	*Phragmites spp.*	1	1168*	18.3	6.0
	Typha spp.	1	1343*	18.9	7.4
	Mean	**1**	**1255**	**18.6**	**6.7**
Trees					
	Alnus glutinosa	15	11400***		
	Fraxinus excelsior	40	18800***		
	Wood			18.6	1.0
	Mean	**28**	**15100**	**18.6**	**1.0**

* Avellán and Gremillion (2019). Median value. n° 286 samples for *Phragmites* spp. and n° 217 for *Typha* spp.
** Avellán and Gremillion (2019). Dry raw material
*** Christen and Dalgaard (2013)

The amount of produced biomass is calculated as follows

$$Biomass_{NBS} = mean\ biomass\ production \cdot A_{NBS} \cdot c_{biomass,NBS}$$

Where A_{NBS} is the area of the NBS and $c_{biomass,NBS}$ is the biomass coverage coefficient of the NBS, which is equal to 1 for trees and subsurface flow wetlands, and 0.7[13] for FWS wetlands.

2.1.4.4.2 Biomass as carbon stock (climate change mitigation)

Despite both CWs (Mander et al., 2014; Maucieri et al., 2017) and buffer strips (Vidon et al., 2019) are known to be source of GHGs such as methane (CH_4) or nitrous oxide (N_2O), these ecosystems commonly remain a net sink of CO2e mainly due to the carbon sequestration capacity of the newly produced biomass (Mitch et al., 2013; de Klein and van der Werf, 2014; Maucieri et al., 2017; Cole et al, 2020). Therefore, (aboveground) biomass is assumed as a "proxy" of climate change mitigation ecosystem service of the proposed NBS, also in agreement with the recent report on NBS for Climate Mitigation of the European Commission (2020b).

Carbon stock is calculated in CO2 equivalent (CO2e) from biomass according to the following approach proposed by de Klein and van der Werf (2014)

$$CO2e = biomass_{NBS} \cdot c_1 \cdot c_2$$

Where c_1 and c_2 are conversion factors taken from De Klein and van der Werf (2014) and equal to 0.44 $g_C/g_{d.w.}$ and 3.7 g_{CO2e}/g_C, respectively. Therefore, the biomass is calculated at the ages of max. biomass, which are taken from the mean values reported in **Table 40**, i.e. equal to 1 for wetland plants[14] and 28 for trees.

2.1.4.4.3 Biomass as energy source

Following the methodology proposed by Avellán and Gremillion (2019), the energy value of the NBS biomass is estimated by calculating the high-heating value (HHV), i.e. a way to estimate the energy value for direct combustion, expressed as energy yield with units of energy per unit mass. The values selected for the different types of biomass are reported in **Table 40**. Therefore, the energy side-benefit is calculated as follows

$$Energy = \frac{biomass_{NBS}}{age\ of\ max.biomass\ growth} \cdot HHV \ \cdot 20$$

Contrarily to biomass for carbon stock benefit, the energy benefit is calculated for an equal time span for both wetlands and trees, assumed equal to 20 years[15]. All the effect on HHV related to different pre-treatments of the raw material (e.g. chopping) or to different energy reuse (e.g. biogas) are neglected, for sake of simplicity. In other words, the "proxy" used to evaluate the energy value of the biomass is independent of the energy reuse chain[16]. In order to allow a proper mechanization of harvesting operations, buffer strips must have a minimum width of 5 m in case of biomass use for energy purposes (Ferrarini et al.; 2017).

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[13] The ratio between area with emergent vegetation and open water (or area planted with floating or submerged species) can vary in FWS, depending on the different objectives of the wetlands. Here, an average single value of 70% was assumed according to those suggested by Kadlec and Wallace (2009) for FWS targeting water pollution control, since higher ratios have not shown beneficial effects in terms of treatment performance and could risk developing excessive *Lemna* spp (high nutrient content in treated ww). Even if a lower ratio could be more beneficial for biodiversity support and less for biomass production, a constant value is here assumed in order to limit the number of variables for the NBS typology classification.

[14] Following a conservative assumption, the carbon stock capacity of the wetland plant is considered for only one year. Therefore, this assumption does not consider, for sake of simplicity, different carbon stock performance due to different operational and management practices. Indeed, reed can be either harvested (typically once per year after 2-3 years from the start-up), as usually done for subsurface flow wetlands, or left into the wetland system, where the biomass is estimated to decompose in about one year (Kayranli et al., 2010), leading to a complex soil C sequestration process in case of FWS systems, due to the lower decomposition rate of the anaerobic environment into the soil (Mitsch et al., 2013). If harvested, the reed stock capacity could be considered for every year (as assumed, for instance, by de Klein and van der Werf, 2014), greatly increasing the C stock capacity of a wetland system, even if a proper end-of-waste should be defined (e.g., if the harvested reed is disposed of in an incinerator, the C stock will be lost). To sum up, one year of accumulation of biomass for wetland plants is a reasonable assumption as a "proxy", even if the full potential of CW as NBS for C sequestration could be underestimated.

[15] These assumptions consider the wetland environment capable of producing biomass for energy demand every year, i.e. that the O&M of reed harvesting in wetlands is done every year

[16] Many literature studies have highlighted technical issues related to a cost-effective reuse of the biomass, especially in terms of transportation, stock, and position of the power plants (Ferrarini et al., 2017; Avellán and Gremillion, 2019). For sake of simplicity, these aspects are here neglected. If the opportunity map evidences a potential interest in the energy value of the produced biomass in a particular European region, a detailed study on the most effective biomass supply chain is mandatory (e.g., Recchia et al., 2010).

As reviewed by Avellán and Gremillion (2019), HHV is not the only aspect that defines the quality of a biomass for energy purposes. The ash content in case of direct combustion is also a useful indicator. Wetland biomass has a higher ash content than wooded biomass (**Table 40**), leading to problems in case of direct combustion such as inefficient energy production, maintenance problems, and respiratory health issues. Densification processes (e.g. pellet, briquettes) can limit the issues related to high ash content, but they will increase the cost and complexity of energy delivery. Therefore, ash content can be considered as a "proxy" of biomass produced for energetic purposes that is easy to reuse. Thus, the technical issues related to ash content is assessed through expert judgment based on literature evidence (**Table 40**); the value function is an ordinal value function, with a negative orientation, and is expressed by an indicator ranging between 0 (best performance) and 1 (worst performance), as follows:

Technical issues related to ash content (from best to worst performance)	**Scores**
Tree biomass	0
Wetland biomass	1

2.1.4.4.4 Climate change mitigation vs. Energy

Both wetlands and trees are able to accumulate a significant amount of biomass. However, the fate of the biomass influences the different benefits. Indeed, a biomass from which energy is produced from direct combustion cannot provide the C stock benefit (since the stocked CO2 is eventually released back into the atmosphere), and vice versa. Therefore, climate change mitigation and energy side-benefits defined here, relying both on biomass only, must be considered mutually exclusive, i.e. either the biomass is considered for climate change mitigation or for energy production.

2.1.4.5 Nuisance

NBS in agricultural landscape, besides providing important benefits, may entail some significant drawbacks. Wetlands located near villages may raise concerns linked to the increase of mosquitos or other unwanted insects. Manure treatment ponds create problems of odor. Wooded buffer strips could shade portions of cultivated fields or increase the proliferation of weeds, reducing the crop productivity. More generally, any NBS implemented in an intensive farming landscape can be considered a problem for highly mechanized farming practises.

Only recently has the acceptance of NBS been the subject of scientific sociological research, however most of the studies concern urban NBS (Haase et al. 2017; Anguelovski et al 2018; Frantzeskaki 2019). Even though the first schemes and programs to promote NBS in agricultural contexts to control diffuse pollution date back to the mid-1990s only in the last 15 years have few sociological studies been done to investigate the interest of local communities towards NBS and how the new rules and incentive schemes were perceived by farmers.

Several studies just analysed the knowledge of the ecosystem services concepts and NBS among different social stakeholders of the rural context (Wagner 2008, Qiu et al 2014).

Atwell et al (2009) investigated the tentative re-integration of perennial vegetation (e.g., cover crops, pastures, riparian buffers, and restored wetlands), in the US Corn Belt. Through the analysis of 33 in-depth interviews, their study indicates that the adoption of conservation practices is based not only on immediate profitability but also on the interaction between contextual factors at three distinct levels of the system:

1. compatibility with farm priorities, profitability, practices, and technologies;
2. community-level reinforcement through local social networks, norms, and support structures;

3. consistent, straightforward, flexible, and well-targeted incentives and regulations issued by regional institutions.

Interviewees suggested that "*the multiscale drivers that currently support the continued expansion of row crop production could be realigned with conservation objectives in landscapes of the future.* [...] *Adaptation of social actors through collaborative learning at the community level may be instrumental in brokering the sort of multiscale system change that would lead to more widespread adoption of perennial cover types in the Corn Belt*".

Buckley et al (2012) examined the willingness of farmers to adopt buffer strips on agricultural land, by interviewing 247 farmers in 12 catchments (approximately 4–12 km^2) in the Republic of Ireland. The survey was based on the proposal to install a 10 m deep riparian buffer zone on a five year scheme. The results from this analysis indicated that **famers' willingness to supply a riparian buffer zone depended on a mix of economic, attitudinal and farm structural factors**. A total of **53% of the sample indicated a negative preference for provision**. Most frequently farmers not willing to adopt NBS motivated their choices by saying that "*the buffer zone would interfere with their current system of farming or had concerns around nuisance effects such as potential proliferation of weeds in the designated area*".

A number of a priori independent variables could be expected to affect the probability that a farmer will be willing to participate in the proposed scheme, including **environmental protection attitude**, **experience of agri-environment schemes**, **opportunity cost for agriculture** and **motivation to follow the advice of regulatory agencies**.

Unfortunately, none of the above mentioned variables can be estimated and mapped to use it as a "proxy" information of the possible nuisance of the NBS for the local community in a spatial MCA. To estimate the possible nuisance effect of the different NBS and their spatial variation, the expert judgement was adopted, based on the experience of the study team. In the following table the nuisance effect was estimated for each NBS on a scale from 0 (no nuisance) to 1 (maximum nuisance), and possibly scaled according to spatial criteria.

Table 41. Value function for nuisance expert-based evaluation

NBS category	NBS type	Nuisance motivation	Quantification
A: Manure-derived wastewater and sludge	Subsurface Constructed wetlands (SSF CWs)	Odor, mosquitos	0
	Free water surface (FWS)	Odor, mosquitos	0.3 in a buffer of 100 m from urban settlements
	Waste stabilization ponds (WSP) or lagoons	Odor, mosquitos	1 in a buffer of 100 m from urban settlements, 0.5 in a buffer of 500 m from urban settlements
B: Landscape elements for diffuse sources of pollution	Wetlands	Obstacle to farming practices	0.2
	Vegetated ditches	Obstacle to farming practices	0.5
	Wooded linear buffer strips	Obstacle to farming practices,	0.8

NBS category	NBS type	Nuisance motivation	Quantification
		shading, weeds	
	Herbaceous linear buffer strips	Obstacle to farming practices, weeds	0.3
C: Landscape elements for water retention and resilience to climate change	Ponds, wetlands, marshes	Obstacle to farming practices	0.2
	Infiltration wood	Obstacle to farming practices, shading	0.3
	Detention basins	Obstacle to farming practices	0

Among the different NBS the one showing the highest value (1) in the "nuisance" ranking is the manure waste stabilization pond located in the vicinity (in a range of 100 m) of a human settlement (note that country regulations limiting the possibility of building manure treatment systems at a given distance from settlements has not been considered). Linear NBS, such as buffer strips or vegetated ditches, are generally more disturbing to farming practice compared to areal NBS, as they interrupt the field continuity. Wooded buffer strips were estimated at 0.8 in the nuisance ranking. A nuisance value of 0.5 has been estimated for vegetated ditches and for manure waste stabilization ponds located within a 500 m radius of a human settlement. Free water wetlands for manure wastewater treatment, herbaceous buffer strips and infiltration woods were estimated at 0.3. Ponds, wetlands, and marshes, both for diffuse pollution control and for water storage or infiltration were estimated at 0.2. Manure Subsurface Constructed wetlands together with any kind of manure treatment system located more than 500 m from human settlements and detention basins were considered fully acceptable by the local community (ranking 0).

2.1.4.6 Landscape, amenity, microclimate enhancement, attractiveness

NBS create new ecosystems that, beside environmental benefits, provide recreation and cultural values including scenic views, aesthetics, open-spaces and leisure opportunities to surrounding residents. The social benefits of NBS, however, depend on the ecosystem typology and the human community involved: wetlands, for example, are perceived as high value ecosystems by the urban population (Russi et Al.2013; Gao 2010) but for the rural environment the presence of wetlands is associated with lower residential property values (Bin and Polasky 2005). Wooded buffer strips, according to Borin et Al. (2010), are perceived by different kinds of interviewed people as an improvement to the aesthetic amenity of the landscape.

The assessment of NBS social benefits could present a high level of uncertainty. Moreover, no published study on social aspects could be found (even grey papers) for some kind of NBS ecosystem (e.g. reed bed). Hence, a value function for the potential social benefits of NBS was developed in the present study, developed on the following choices and assumptions:

— The criterion selected to quantify the social benefit of NBS is the "**accessibility for recreation**", one of the key criteria chosen to assess socio/cultural ecosystem services by the UK “National Ecosystem Assessment” (Church et al. 2017) which is also easily quantifiable and predictable.

- Not all the NBS considered in the present study are interesting for recreation. Therefore, the “recreational” social benefit was considered negligible for the following NBS:
    - **Category A NBS (ponds and wetlands)**: being manure treatment wetlands, they will most likely not be accessible to the general public;
    - **Vegetated ditches**: have no recreational interest
    - **Herbaceous buffer strips**: have no recreational interest
- Two classes of NBS were selected: NBS creating aquatic ecosystems (all kind of wetlands and ponds and integrated buffer strips); NBS creating wooded habitats (wooded buffer strips and infiltration woods). The recreational attractiveness of aquatic ecosystems was considered to be greater compared to wooded habitat strips or patches: the social benefit of an accessible wooded habitat was considered to be 50% of the social benefit of a wetland or a pond.

Most of the research done on the **accessibility for recreation service** concerns urban contexts (Grunewald et al 2017; Raymond et al. 2017) where residents expect to find recreational areas at a walking distance from home (300-500 m). However, the present study is focused on rural areas, where people living in nearby villages or urban suburbs can use areas located at longer distances for recreational purposes (1 Km is the minor range but even 10 km might be considered an accessible distance)[17]. Therefore, a distance range of 2 km from the NBS can be considered conservative to identify the possible users of the area for recreation.

Two attributes were adopted to assess the landscape/recreation value of the NBS: the intrinsic attractiveness of the NBS and the potential population P that can benefit from it because it lies in a suitable accessibility zone (population limited by a saturation effect). Hence the size of the NBS was ignored.

Following the scheme presented by Nardini (1988), the intrinsic attractiveness therefore plays the role of an intensive variable, while population plays the role of an extensive variable, thus “abundance” and a multiplicative structure appears as a reasonable choice to represent the quality-abundance combination. Formally:

$$NBS_{social\ benefit} = NBS_{intrinsic\ attractiveness} \times abundance$$

Where

- $NBS_{intrinsic\ attractiveness}$ is evaluated with an expert-based value function, relying on literature analysis; the value function is an ordinal value function, with a positive orientation, and expressed by an indicator ranging between 0 and 1, as follows:

Intrinsic attractiveness (from worst to best performance)	**Scores**
None	0
Wooded area	0.5
Wetland area (excluded NBS A)	1

- $abundance$ represents the accessibility of the area; it’s estimated with the amount of population that can benefit from the NBS, defined as the population living in a pre-defined neighboring zone (e.g. a circle determined by a parameter; or the max length of roads/trail

[17] According to the results of the analysed case studies, e.g. Feasibility Study “Nature-based solutions for climate change adaptation and water pollution in agricultural regions”, Lot 5: LDP in a continental environment.

paths leading to it from nearby urban centers), in this case assumed area with a radius of 2 km.

2.1.4.7 Managed Aquifer Recharge (MAR) in saline aquifers

Percolation ponds are gaining more and more interest as methods of managed aquifer thanks to their cheapness and simplicity of construction and management, MAR systems are also considered among the solutions to contrast saline intrusion in coastal aquifers (Dillon 2005). However, based on the experience of Christy et al., 2017 and Raicy et al., 2020, who investigated the effect of a percolation pond positioned 3.8 km west of the Bay of Bengal, India, for the scale of the interventions of the farm ponds proposed in this study, negligible effects are expected on the quality of groundwater in coastal aquifers. Better results can be obtained with more diffuse solutions or different MAR methods. Therefore, in light of these observations, it was decided for sake of simplicity to neglect this benefit.

2.2 Building of relationships for costs

2.2.1 Methodology overview

The construction of relationship between the dimensional parameters of the NBS (e.g. area, volume) and the regional parametric costs, is based on the analysis of the bill of quantity of the NBS analysed in the European feasibility studies[18]. <u>In particular, the Hybrid CWs of the Slovenian feasibility study were considered for the construction of the CAPEX and OPEX equations for the SF, SSF, Pond and VD systems.</u> For the buffers, the bill of quantity and maintenance costs present in the feasibility study regarding Lot 5 and 6 were considered.

The aim was to create an equation between the main expenditure items for the construction of the NBS (e.g. excavation, embankment, filling medium, waterproofing) and the respective local parametric costs. The corrective coefficients C1 and C2 consider respectively the minor items cost and the presence of primary treatments. Costs for land acquisition and technical investigation and consultancy were also considered in the equation. The variables of the equations are:

- Excavation;
- Embankment;
- Filling medium;
- Waterproofing;
- Land acquisition;
- Technical investigation and consultancy.

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[18] Synthesis centres on innovative wastewater treatment: feasibility studies in the Lower Danube - Lot1: Slovenia, Slovakia, Czech Republic, Hungary, Bosnia-Herzegovina, Montenegro, Croatia

Feasibility study for the management of wastewater from a scout conference in the territory of Wyspa Sobieszewska – Jamboree 2023

Nature-based solutions for climate change adaptation and water pollution in agricultural regions - Lot 5: LDP in a continental environment

Nature-based solutions for climate change adaptation and water pollution in agricultural regions - Lot 6: LDP in a Mediterranean environment

Nature-based solutions for climate change adaptation and water pollution in agricultural regions - Lot 2: TSM in a continental environment

The equation has the following form:

$$\boldsymbol{CAPEX = WORKING\ COST + LAND\ ACQUISITION + TECHNICAL\ INVESTIGATION\ AND\ CONSULTANCY}$$

The $WORKING\ COST$ equation has the following form:

$$WORKING\ COST = \Big((Cs \cdot V) + (Ce \cdot V) + (Cf \cdot Vf) + (Cw \cdot A) + \big(n_{trees} \cdot A\ \cdot p_{pers}\big)\Big) \cdot C1 \cdot C2$$

where:

— Cs is the parametric cost for the excavation (€/m^3);

— Ce is the parametric cost for the embankment (€/m^3);

— Cf is the parametric cost for the filling medium (€/m^3);

— Cw is the parametric cost for the waterproofing (€/m^2);

— A is the area (m^2);

— V is the volume (m^3);

— Vf is the filling medium volume (m^3);

— $C1$ is a corrective coefficient, as function of the area;

— $C2$ is a corrective coefficient for the primary treatments cost.

— n_{trees} is the parametric number of equivalent personnel working hours for tree planting, as function of the buffer strip area (h/m^2);

— p_{pers} is the parametric cost of personnel (€/h).

The $LAND\ ACQUISITION$ equation is:

$$LAND\ ACQUISITION = Cl \cdot Al$$

where:

— Cl is the parametric cost for the land acquisition;

— Al is the acquisition area, obtained by multiplying the area of the system by a coefficient equal to 2 for Ponds, SFs and SSFs. The area is equal to the 1 m wide perimeter area around the drainage canal for VDDs and Buffers (m^2);

The $TECHNICAL\ INVESTIGATION\ AND\ CONSULTANCY$ equation is:

$$TECHNICAL\ INVESTIGATION\ AND\ CONSULTANCY = p \cdot WC$$

where:

— WC is the Working cost of the system (€);

— p is the percentage of the working cost that corresponds to the technical investigation and consultancy costs, equal to 15% for SFs, SSFs and Ponds. It is equal to 10% for VDs and Buffers.

The equation for the definition of the total maintenance costs of the NBS presents only the variable of the number of annual working hours of the personnel for the check, green maintenance and reed harvesting. This variable multiplied by the hourly cost of the personnel and by the respective corrective coefficients C1 and C2, defines the operation and maintenance cost system. The relationship has the following form:

$$\boldsymbol{OPEX = (n_{checking} + n_{reed+green\,maint}) \cdot A \cdot p_{pers} \cdot C1 \cdot C2}$$

where:

— $n_{checking}$ is the parametric number of equivalent personnel working hours for the annual checking, as function of the NBS area (h/m^2/y);

— $n_{reed+green\,maint}$ is the parametric number of equivalent personnel working hours for the annual reed and green maintenance, as function of the NBS area (h/m^2/y);

— p_{pers} is the parametric cost of personnel (€/h);

— $C1$ is a corrective coefficient, as function of the area;

— $C2$ is a corrective coefficient for the primary treatments maintenance cost.

2.2.2 Verification of the cost functions

The relationships obtained for the CAPEX and OPEX were tested on the NBS of the feasibility study of Lot 5 and Lot 6.

2.2.2.1 CAPEX verification

For the studied FWS of Lot 5 the main variables to consider are excavation and earthmoving. The parametric costs of excavation and earthmoving derive from the 2018 price list of the Veneto region, and amount to 5.51 €/m^3 and 10.8 €/m^3 respectively. To define the excavation and earthmoving volume, an excavation depth of 0.8 m is assumed. The corrective coefficient C1 is calculated using formula for SF in **Errore. L'origine riferimento non è stata trovata.** in ANNEX 9. For the two FWSs, there are no primary treatments, so the coefficient C2 can be neglected.

The Linear Park of Marina di Latina present in Lot 6 is characterized by two HFs and two FWSs, each with an area of approximately 0.1 ha. The parametric costs of excavation and earthmoving derive from the 2016 price list of the Lazio Region, respectively of 5.11 €/m^3 and 4.09 €/m^3. For the calculation of the excavation and earthmoving volume, an excavation depth of 0.8 m is assumed. For the HF, the costs variables of the filling medium and waterproofing were also considered. The coefficient C1 for the HF and FWS was calculated according to the formula for SSF and SF respectively, in **Errore. L'origine riferimento non è stata trovata.** (ANNEX 9). The coefficient C2 is negligible. The result are reported in **Table 42**.

The parametric cost assumed for the land acquisition is equal to 20 €/m^2. The multiplicative coefficient of the area, to calculate the land acquisition area, is equal to 2. The technical investigation and consultancy costs are assumed to be equal to 15% of the working cost.

Table 42: CAPEX verification

	Unit	Lot 5 - Salzano	Lot 5 - Rusteghin	Lot 6 - Linear Park of Marina di Latina		
Excavation	€/m3	5.51	5.51	5.11	5.11	
Embankment	€/m3	10.8	10.8	4.09	4.09	
Depth	m	0.8	0.8	0.8	0.8	
Filling medium	€/m3			20		

	Unit	Lot 5 - Salzano	Lot 5 - Rusteghin	Lot 6 - Linear Park of Marina di Latina		
Waterproofing	€/m2			13		
Land acquisition	€/m2	20	20	20	20	20
Percentage Technical investigation and consultancy	%	15%	15%	15%	15%	15%
Coeff. Land area		2	2	2	2	2
WORKING COST	€	1,551,563.54 €	642,894.25 €			471,377.45 €
Land acquisition	€	569,415.50 €	448,618.76 €			
Technical investigation and consultancy	€	77,578.18 €	38,901.40 €			7,560.26 €
ECONOMIC FRAMEWORK	€	**2,198,557.22 €**	**1,130,414.41 €**			**478,937.71 €**
C1		2.1	2.6	1.9	3.4	
		SF	**SF**	**SSF**	**SF**	**TOTAL**
Area	ha	21.6	3.5	0.2	0.2	0.4
	m2	216000.00	35000.00	2000	2000	4000
Excavation	€	952,128.00 €	154,280.00 €	8,176.00 €	8,176.00 €	16,352.00 €
Embankment	€	1,866,240.00 €	302,400.00 €	6,544.00 €	6,544.00 €	13,088.00 €
Filling medium	€			32,000.00 €		32,000.00 €
Waterproofing	€			26,000.00 €		26,000.00 €
Total cost		2,818,368.00 €	456,680.00 €	72,720.00 €	14,720.00 €	87,440.00 €
WORKING COST	€	**6,006,510.55 €**	**1,171,806.44 €**	**138,343.37 €**	**50,575.66 €**	**188,919.03 €**
Land acquisition	€	8,640,000.00 €	1,400,000.00 €	80,000.00 €	80,000.00 €	160,000.00 €
Technical investigation and consultancy	€	900,976.58 €	175,770.97 €	20,751.51 €	7,586.35 €	28,337.85 €
ECONOMIC FRAMEWORK	€	**15,547,487.13 €**	**2,747,577.40 €**	**239,094.88 €**	**138,162.01 €**	**377,256.89 €**
Working cost error%	%	**74%**	**45%**			**-150%**
Economic framework error %	%	**86%**	**59%**			**-27%**
Parametric cost	€/m2	71.98 €	78.50 €	119.55 €	69.08 €	94.31 €

The calculated working costs are on average **10%** lower than the original working costs, while the economic framework cost is on average **39%** higher than the original costs.

2.2.2.2 OPEX verification

In the OPEX equation, the only variable assumed is the number of personnel working hours for the check and green maintenance. The number of hours for green maintenance is obtained by dividing the green maintenance cost expressed in €/y by the hourly cost of personnel in €/h. The total working hours of the staff are obtained by adding the hours for the check and maintenance of the green. The value obtained is multiplied by the hourly cost of the personnel by the corrective coefficients C1, according to the SF formula in **Errore. L'origine riferimento non è stata trovata.** (ANNEX 9), and C2, equal to **1.9.** The result are reported in **Table 43**.

Table 43: OPEX verification

	Unit	Salzano	Rusteghin	Basin A - Villa Fogliano	Linear Park of Marina di Latina
Area	m2	216000	35000	8500	4000
Personnel	€/h	10	10	25	25
Time	h	3	3	3	3
Visit	n°/y	4	4	2	2
Total hours	h/y	12	12	6	6
Green maintenance	€	587.40 €	330.00 €	198.00 €	291.83 €
	h/y	58.74	33.00	7.92	11.67
C1		1.86	1.71	1.61	1.55
C2		1.87	1.87	1.87	1.87
Calculated_cost		**2,465.12 €**	**1,441.94 €**	**1,044.67 €**	**1,281.04 €**
Real_cost		**1,682.49 €**	**1,146.80 €**	**1,398.96 €**	**859.83 €**
Error %		32%	20%	-34%	33%

The calculated maintenance costs are on average **13%** higher than the original maintenance costs.

2.2.2.3 Summary of the cost equations

The variables of the CAPEX equations are:

— Cs is the parametric cost for the excavation (€/m^3);

— Ce is the parametric cost for the embankment (€/m^3);

— Cf is the parametric cost for the filling medium (€/m^3);

— Cw is the parametric cost for the waterproofing (€/m^2);

— Cl is the parametric cost for the land acquisition (€/m^2);

— WC is the Working cost of the system (€);

— A is the area (m^2);

— Al is the acquisition area (m^2);

— V is the volume (m^3);

— Vf is the filling medium volume (m^3);

— $C1$ is a corrective coefficient, as function of the area;

— $C2$ is a corrective coefficient for the primary treatments cost;

— n_{trees} is the parametric number of equivalent personnel working hours for tree planting, as function of the buffer strip area (h/m^2);

— p_{pers} is the parametric cost of personnel (€/h).

— p is the percentage of the working cost that corresponds to technical investigation and consultancy costs, equal to 15% for SSFs, SFs and Ponds, 10% for VDDs and Buffers;

Table 44. CAPEX equations

System	CAPEX		
	Equation	**c1**	**c2**
SSF	CAPEX=((Cs*V)+(Ce*V)+(Cf*Vf)+(Cw*A))*C1*C2)+(Cl*Al)+(p*WC)	C1=3.7136*Area^(-0.088)	1.4
SF	CAPEX=((Cs*V)+(Ce*V)+(Cw*A))*C1*C2)+(Cl*Al)+(p*WC)	C1=7.46*Area^(-0.102)	1.5
Pond	CAPEX=((Cs*V)+(Ce*V)+(Cw*A))*C1)+(Cl*Al)+(p*WC)	C1=7.819*Area^(-0.189)	-
VD	CAPEX=((Cs*V)+(Ce*V))*C1)+(Cl*Al)+(p*WC)	1.7	-
Buffer	CAPEX= ((Cs*V)+(Ce*V)+n_trees*p_pers*A)+(Cl*A)+(p*WC)	-	-

The variables used are indicated in **Table 45**.

Table 45. Variables used in the CAPEX equations

	CAPEX				
	SSF	**SF**	**Pond**	**VD**	**Buffer**
Cs	X	X	X	X	X
Ce	X	X	X	X	X
Cf	X				
Cw	X	X	X		
Cl	X	X	X	X	X
WC	X	X	X	X	X
A	X	X	X		
V	X	X	X	X	X
Vf	X				
Al	X	X	X	X	X
p	X	X	X	X	X
c1	X	X	X	X	
c2	X	X			

The variables of the OPEX equations are:

- $n_{checking}$ is the parametric number of equivalent personnel working hours for annual checking, as function of NBS area (h/m^2/y);
- $n_{reed+green\ maint}$ is the parametric number of equivalent personnel working hours for the annual reed and green maintenance, as function of NBS area (h/m^2/y);
- *C1* is a corrective coefficient, as function of the area;
- *C2* is a corrective coefficient for the primary treatments maintenance cost.

Table 46. OPEX equations

System	OPEX

	Equation	c1	c2	n_checking	n_green,reed
SSF	OPEX=n*p*C1*C2	C1=1.1658*Area^0.0239	1.8	12.016*Area^0.758	0.09
SF	OPEX=n*p*C1*C2	C1=1.0585*Area^0.0461	1.9	12.016*Area^0.758	0.07
Pond	OPEX=n*p*C1	C1=0.332*Area^0.2637	-	12.016*Area^0.758	-
VDD	OPEX=n*p*C1	1.5	-	12.016*Area^0.758	0.01
Buffer	OPEX=n*p*C1	1.6	-	0.01	-

The variables used are indicated in **Table 45**.

Table 47. Variables used in the OPEX equations

OPEX					
	SSF	**SF**	**Pond**	**VDD**	**Buffer**
n_checking	X	X	X	X	X
n_green,reed	X	X		X	
p	X	X	X	X	X
c1	X	X	X	X	X
c2	X	X			

2.3 Building of relationships for benefit monetization

The economic valuation of NBS benefits followed a detailed procedure: a summary of the method is included in this section but a more detailed methodological explanation of all the steps involved can be found in ANNEX 11.

First of all, a **literature review** was carried out with the aim of recognizing the most common benefits (Ecosystem Services) deriving from the NBS implementation. 19 benefits were identified which were filtered out to select the most appropriate ones in the rural context. Only for the selected environmental and social benefits (9 categories out of 19), was a research carried out on existing economic evaluation methods to proceed with the Value Transfer (VT). The list of selected benefits for each NBS group are summarised in **Table 48**.

Table 48. List of ecosystem services selected for the value tranfer

NBS type	Benefit JRC 0640	Type of benefit	Ecosystem services CICES classification	
			Code from CICES V 4.3	Code from CICES V 5.1
NBS A	Water Quality	Main Benefit	2.3.4.1	2.2.5.1
	Biodiversity support	Side benefit	2.3.1.2	2.2.2.3
	Climate change (GHG, NH3 Volatilization)	Side Benefit	2.3.5.1	2.2.6.1
	Nuisance	Side Benefit	2.1.2.3	2.1.2.1; 2.1.2.2; 2.1.2.3
	Energy from bioethanol	Side benefit	N/A	1.1.5.3
	Energy from wood production	Side benefit	1.1.1.3	1.1.5.1; 1.1.5.2
NBS B	Water Quality	Main Benefit	2.3.4.1	2.2.5.1
	Biodiversity support	Side benefit	2.3.1.2	2.2.2.3
	Landscape amenity, microclimate enhancement, attractiveness	Side benefit	3.1.2.5	3.1.2.4
	Climate change and GHG	Side benefit	2.3.5.1	2.2.6.1
	Energy from bioethanol	Side benefit	N/A	1.1.5.3
	Energy from wood production	Side benefit	1.1.1.3	1.1.5.1; 1.1.5.2
NBS C	Flood risk	Main Benefit	2.2.2.2	2.2.1.3
	Droughts mitigation	Main Benefit	1.1.2.1; 1.2.2.1	4.2.1.1; 4.2.1.2
	Water Quality	Side benefit	2.3.4.1	2.2.5.1
	Biodiversity Support	Side benefit	2.3.1.2	2.2.2.3
	Landscape, amenity, microclimate enhancement, attractiveness	Side benefit	3.1.2.5	3.1.2.4

NBS type	Benefit JRC 0640	Type of benefit	Ecosystem services CICES classification	
			Code from CICES V 4.3	Code from CICES V 5.1
	Climate change mitigation	Side benefit	2.3.5.1	2.2.6.1
	Energy from bioethanol	Side benefit	N/A	1.1.5.3
	Energy from wood production	Side benefit	1.1.1.3	1.1.5.1; 1.1.5.2
	Saline intrusion mitigation	Side benefit	N/A	N/A
	Subsidence mitigation	Side benefit	N/A	N/A

Value transfer (VT) is an economic valuation method that can be applied to ecosystems, or to the goods and services of an ecosystem. VT provides empirical estimates of the subject of interest, when time, funding or other constraints prevent the use of primary research to generate these estimates. Indeed, it allows extrapolating research results of pre-existing primary studies at one or more *study sites* allowing an indirect estimation of the value of some characteristics of similar unstudied policy sites (Rolfe *et al.*, 2015). Among the available VT techniques, the Adjusted Unit Value Transfer was considered the most appropriate for the study aim, i.e. a VT of ES provided by NBS at European scale.

The **study sites** were collected as candidates according to the two following criteria: sites located in regions with socio-economic characteristics similar to Europe (i.e. Europe and North America) and focused on environmental goods and services relevant to the policy site. The collected study sites were organised in a dataset (Attachment 6). From the list of comparable values, the most suitable candidates for the transfer were selected. The choice was based on the following criteria:

- values expressed in spatial unit (e.g., m^2, hectare) per year were preferred;
- study sites with the most similar characteristics were preferred;
- more recent studies were preferred.

A five step method was developed to **adjust the economic values** from those of the study site to those used for the policy sites of interest (i.e. a particular point in EU with a particular NBS). The methodology described followed the approach proposed by Brander (2013) and permitted to account for inflation, to control for differences in price levels, to control the effect of income on the demand, to take into account the different NBS and value of ecosystem services and, finally, to convert into $euro_{2018}$. The five steps are summarised and described in **Table 49**.

Table 49. Steps to calculcate the adjusted VT of an ecosystem service for the policy site of interest

Step	Year	Currency	Country	NBS	Description
0	year of the latest update of the value	currency used in the latest update of the value	study site	study site	Original value from the study site, as reported in Value Transfer dataset (Attachment 6)
1	2018	currency used in the latest update of the value	study site	study site	To account for inflation, the values have been adjusted to the general price level of the same year. To compare the ecosystem service values computed in different years, they were harmonized using the annual

Step	Year	Currency	Country	NBS	Description
					Consumer Price Index (OECD, 2020), with 2015 as the base year, transforming the values into the latest available "original" currency, which corresponds to the year 2018.
2	2018	$	study site	study site	To control for differences in price levels, the values were transformed into US$ 2018, using the 2018 exchange rates (OECD, 2018) in order to proceed with the next step (which implies using a monetary measure expressed in USD).
3	2018	$	study site	policy site	To transfer the value to the NBS of interest to the policy site, a correction factor was used, capable of taking into account the uncertainties due to different NBS types, evaluation methods, and indicators used to estimate the value of the ecosystem service
4	2018	$	policy site	policy site	To control the effect of income on the demand and value of ecosystem services, estimates were adjusted for the differences in Gross Domestic Product per capita based on Purchasing Power Parity (PPP) (WB, 2020) between study and policy site.
5	2018	€	policy site	policy site	The values were finally transformed into euro2018, using exchange rates (OECD, 2018).

As stated by Schmidt et al. (2016), assigning a monetary value to nature is not considered to be absolute, but is rather an indication referring to a particular area, a given time period, a specific beneficiary group, depending on the valuation context and use. Adjustments may not be enough to remove transfer errors so, consistent with Brander's (2013) guidelines, an additional correction factor was applied to all of them; it is a measure of monetization reliability, inspired by CIRIA's Benefits Evaluation of SuDS Tool (B£ST). The **correction factor used in step (3)** was calculated considering three different attributes

— (a) NBS type

— (b) Monetary valuation technique used for the economic value calculation

— (c) Indicator used to quantify the magnitude of the benefits

A scoring methodology was defined for each attribute of the correction factor, reported in **Table 50**.

Table 50. Scores associated to attributes used to define the correction factor used in VT step (3)

	Correction factor attributes	Type	Evaluation method
(a)	NBS type	Categorical Score: 1-5	Expert-based evaluation 1=very low 2=low 3=sufficient 4= high 5= very high
(b)	Monetary valuation technique	Binary Score: 0-1	0=Value Transfer

	Correction factor attributes	Type	Evaluation method
			1=Cost-based/direct market pricing if per hectare terms; Contingent Valuation/Choice experiment if per beneficiary terms
(c)	Indicator	Binary Score: 0-1	Expert-based evaluation 0=low reliability 1=high reliability

On the basis of the attribute scores, the correction factor is calculated as follows:

Scores (i) + (ii) + (iii)	VT Correction factor
7	1
6	0.9
5	0.8
4	0.7
<4	0.5

In conclusion, **relationships for the VT of ecosystem services** for different NBS across Europe are calculated as follows

$$VT^{PS}_{NBS,2018,€} = VT^{SS}_{NBS,2018,\$} \cdot \frac{GDP^{PS}_{2018}}{GDP^{SS}_{year\ of\ VT}} \cdot c_{\$\ to\ €,2018}$$

where:

- $VT^{PS}_{NBS,i,2018,€}$ is the value transfer of the ecosystem service in the policy site (PS) for the NBS of interest in 2018, expressed in € (VT steps 1+2+3+4+5)
- $VT^{SS}_{NBS,2018,\$}$ is the value transfer of the ecosystem service in the study site (SS) for the NBS of interest in 2018, expressed in $ (VT steps 1+2+3)
- GDP^{PS}_{2018} is the Gross Domestic Product (GDP) per capita based on Purchasing Power Parity (PPP) for the PS country (VT step 4)
- $GDP^{SS}_{year\ of\ VT}$ is the GDP per PPP for the SS country (VT step 4)
- $c_{\$\ to\ €,2018}$ is the Dollar to Euro exchange rate in 2018, equal to 0.87097 €/$[19] (VT step 5)

The variables needed for relationships (c) are summarised in **Table 51**, while details on the correction factor used to estimate the NBS value transfer are reported in ANNEX 11.

[19] https://it.exchange-rates.org/Rate/USD/EUR/31-12-2018

Table 51. Matrix of variable needed for value transfer of ecosystem services provided by NBS

Ecosystem service	Orient	Study site			NBS value transfer (VT step 3)													Unit
		Country	**Year of ES valuation**	**GDP per capita (PPP) Year of ES valuation**	**NBS A wet. SSF**	**NBS A wet. SF**	**NBS B wet.**	**NBS B VDD**	**NBS B BS-R**	**NBS B BS-G**	**NBS B int. BS**	**NBS C Stor. Pond**	**NBS C Stor. Pond + wet.**	**NBS C MAR pond**	**NBS C MAR pond + wet**	**NBS C MAR dry pond**	**NBS C MAR infiltr. Wood**	
WATER SUPPLY	↑	Spain	2004	26119.79								4396	4396	4396	4396	4396	4396	$/ha/yr
		Poland	2013	24719.25								807	807	807	807	807	807	$/ha/yr
		Spain	2004	26119.79						5470								$/ha/yr
NATURAL HABITAT and BIODIVERSITY SUPPORT	↑	Spain	2004	26119.79	179	286	321	179										$/ha/yr
		UK	2007	35600.01					29	29	32						29	$/ha/yr
WATER QUALITY	↑	Germany	2001	28380.38	4111	4111	4111	4111					4111		4111			$/ha/yr
		Spain	2004	26119.79	2121	2121	2121	2121					2121		2121			$/ha/yr
		US	1998	32853.68					59	107	107							$/ha/yr
CARBON SEQUESTRATION	↑	US	2008	48382.56	140	140	140	100					140		140			$/ha/yr
		UK	2007	35600.01					1974	1974	1974						1974	$/ha/yr
FLOOD RISK	↑	Denmark	2000	28662.09		83	133	83				133	133	133	133			$/ha/yr
		Spain	2004	26119.79							222							$/ha/yr
NUISANCE (ODORS, RUMORS, OBSTACLES TO COMMON FARMING PRACTICES)	↓	Belgium	2008	37883.33	4720	4720	2622	2622				2622	2622	2622	2622			$/house/yr
		Belgium	2008	37883.33														$/house/yr
RECREATION and TOURISM	↑	Spain	2004	26119.79			4003	2224				2224	2224	2224	2224			$/ha/yr
		Denmark	2000	28662.09			5											$/person/visit
		Spain	2007	32438.17			3											$/person/visit
		Spain	2004	26119.79					3901	3901	3901						2167	$/ha/yr
VISUAL IMPACT/AMENITY and AESTHETIC	↑	Spain	2004	26119.79			2252	1408				1408	1408	1408	1408			$/ha/yr
		UK	2007	35600.01						1606							1147	$/ha/yr
AWARENESS/EDUCATION	↑	Greece	2003	23870.16			9											$/person/visit
		Canada	1983	46723.32						10							7	$/person/visit

3 REFERENCES

Peer review papers

Acreman, M. and Holden, J., 2013. How wetlands affect floods. Wetlands, 33(5), pp.773-786.

Alarcon, B., Aguado, A., Manga, R. and Josa, A., 2010. A value function for assessing sustainability: application to industrial buildings. Sustainability, 3(1), pp.35-50.

Alvarez, V.M., González-Real, M.M., Baille, A., Valero, J.M. and Elvira, B.G., 2008. Regional assessment of evaporation from agricultural irrigation reservoirs in a semiarid climate. Agricultural water management, 95(9), pp.1056-1066.

Ambati, R.R., Majumdar, G. and Reddy, A.R., 2011. Validation of farm pond size for irrigation during drought. Indian Journal of Agronomy, 56(4), pp.356-364.

Ameli, A.A. and Creed, I.F., 2019. Does Wetland Location Matter When Managing Wetlands for Watershed-Scale Flood and Drought Resilience?. JAWRA Journal of the American Water Resources Association, 55(3), pp.529-542.

Amell, M.A.N., Awais, M., Ragul, S., Brüggemann, K. and Avellán, T., 2019. Attribute value extraction mechanism of Constructed Wetlands information. MethodsX, 6, pp.1054-1067

Anguelovski, I., Connolly, J. and Brand, A.L., 2018. From landscapes of utopia to the margins of the green urban life: For whom is the new green city?. City, 22(3), pp.417-436.

Annor, F.O., Van De Giesen, N., Liebe, J., Van de Zaag, P., Tilmant, A. and Odai, S.N., 2009. Delineation of small reservoirs using radar imagery in a semi-arid environment: A case study in the upper east region of Ghana. Physics and Chemistry of the Earth, Parts A/B/C, 34(4-5), pp.309-315.

Arora, K., Mickelson, S.K., Helmers, M.J. and Baker, J.L., 2010. Review of pesticide retention processes occurring in buffer strips receiving agricultural runoff 1. JAWRA Journal of the American Water Resources Association, 46(3), pp.618-647.

Atwell, R.C., Schulte, L.A. and Westphal, L.M., 2009. Linking resilience theory and diffusion of innovations theory to understand the potential for perennials in the US Corn Belt. Ecology and Society, 14(1).

Avellán, T. and Gremillion, P., 2019. Constructed wetlands for resource recovery in developing countries. Renewable and Sustainable Energy Reviews, 99, pp.42-57.

Barling, R.D. and Moore, I.D., 1994. Role of buffer strips in management of waterway pollution: a review. Environmental management, 18(4), pp.543-558.

Beckingham, B., Callahan, T. and Vulava, V.M., 2019. Stormwater ponds in the southeastern US coastal plain: hydrogeology, contaminant fate, and the need for a social-ecological framework. Frontiers in Environmental Science, 7, p.117.

Benassi, G., Battisti, C., Luiselli, L. and Boitani, L., 2009. Area-sensitivity of three reed bed bird species breeding in Mediterranean marshland fragments. Wetlands Ecology and Management, 17(5), p.555.

Benassi, G., Battisti, C. and Luiselli, L., 2007. Area effect on bird species richness of an archipelago of wetland fragments in Central Italy. Community Ecology, 8(2), pp.229-237.

Berg, M.D., Popescu, S.C., Wilcox, B.P., Angerer, J.P., Rhodes, E.C., McAlister, J. and Fox, W.E., 2016. Small farm ponds: overlooked features with important impacts on watershed sediment transport. JAWRA Journal of the American Water Resources Association, 52(1), pp.67-76.

Bin, O. and Polasky, S., 2005. Evidence on the amenity value of wetlands in a rural setting. Journal of Agricultural and Applied Economics, 37(1379-2016-112804), pp.589-602.

Borin, M., Passoni, M., Thiene, M. and Tempesta, T., 2010. Multiple functions of buffer strips in farming areas. European journal of agronomy, 32(1), pp.103-111.

Bouwer, H., 2002. Artificial recharge of groundwater: hydrogeology and engineering. Hydrogeology journal, 10(1), pp.121-142.

Brainard, A.S. and Fairchild, G.W., 2012. Sediment characteristics and accumulation rates in constructed ponds. Journal of soil and water conservation, 67(5), pp.425-432.

Brander, L., Brouwer, R. and Wagtendonk, A., 2013. Economic valuation of regulating services provided by wetlands in agricultural landscapes: A meta-analysis. Ecological Engineering, 56, pp.89-96.

Buckley, Cathal, Stephen Hynes, and Sarah Mechan. "Supply of an ecosystem service—Farmers' willingness to adopt riparian buffer zones in agricultural catchments." Environmental Science & Policy 24 (2012): 101-109.

Buraihi, F.H. and Shariff, A.R.M., 2015. Selection of rainwater harvesting sites by using remote sensing and GIS techniques: a case study of Kirkuk, Iraq. Jurnal Teknologi, 76(15).

Calliari, E., Staccione, A. and Mysiak, J., 2019. An assessment framework for climate-proof nature-based solutions. Science of the Total Environment, 656, pp.691-700.

Camnasio, E. and Becciu, G., 2011. Evaluation of the feasibility of irrigation storage in a flood detention pond in an agricultural catchment in Northern Italy. Water resources management, 25(5), pp.1489-1508.

Cao, M., Zhou, H., Zhang, C., Zhang, A., Li, H. and Yang, Y., 2011. Research and application of flood detention modeling for ponds and small reservoirs based on remote sensing data. Science China Technological Sciences, 54(8), pp.2138-2144.

Castaldelli, G., Soana, E., Racchetti, E., Vincenzi, F., Fano, E.A. and Bartoli, M., 2015. Vegetated canals mitigate nitrogen surplus in agricultural watersheds. Agriculture, Ecosystems & Environment, 212, pp.253-262.

Christen, B. and Dalgaard, T., 2013. Buffers for biomass production in temperate European agriculture: A review and synthesis on function, ecosystem services and implementation. Biomass and Bioenergy, 55, pp.53-67.

Cohen, M.J., Creed, I.F., Alexander, L., Basu, N.B., Calhoun, A.J., Craft, C., D'Amico, E., DeKeyser, E., Fowler, L., Golden, H.E. and Jawitz, J.W., 2016. Do geographically isolated wetlands influence landscape functions?. Proceedings of the National Academy of Sciences, 113(8), pp.1978-1986.

Cole, L.J., Stockan, J. and Helliwell, R., 2020. Managing riparian buffer strips to optimise ecosystem services: A review. Agriculture, Ecosystems & Environment, p.106891.

Collins, A.L., Hughes, G., Zhang, Y. and Whitehead, J., 2009. Mitigating diffuse water pollution from agriculture: Riparian buffer strip performance with width. CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources, 4(39), p.p15.

Cooper, C.M., Moore, M.T., Bennett, E.R., Smith, S., Farris, J.L., Milam, C.D. and Shields, F.D., 2004. Innovative uses of vegetated drainage ditches for reducing agricultural runoff. Water Science and Technology, 49(3), pp.117-123.

Christy, R.M. and Lakshmanan, E., 2017. Percolation pond as a method of managed aquifer recharge in a coastal saline aquifer: A case study on the criteria for site selection and its impacts. Journal of Earth System Science, 126(5), pp.1-16.

Crites, Middlebrooks, Reed. 2006 Natural Wastewater Treatment Systems. Taylor & Francis.

De Winnaar, G., Jewitt, G.P.W. and Horan, M., 2007. A GIS-based approach for identifying potential runoff harvesting sites in the Thukela River basin, South Africa. Physics and Chemistry of the Earth, Parts A/B/C, 32(15-18), pp.1058-1067.

de Klein, J.J. and van der Werf, A.K., 2014. Balancing carbon sequestration and GHG emissions in a constructed wetland. Ecological engineering, 66, pp.36-42.

Díaz, F.J., Anthony, T.O. and Dahlgren, R.A., 2012. Agricultural pollutant removal by constructed wetlands: Implications for water management and design. Agricultural Water Management, 104, pp.171-183.

Dillon, P., 2005. Future management of aquifer recharge. Hydrogeology journal, 13(1), pp.313-316.

Dillon, P., Stuyfzand, P., Grischek, T., Lluria, M., Pyne, R.D.G., Jain, R.C., Bear, J., Schwarz, J., Wang, W., Fernandez, E. and Stefan, C., 2019. Sixty years of global progress in managed aquifer recharge. Hydrogeology journal, 27(1), pp.1-30.

Dollinger, J., Dagès, C., Bailly, J.S., Lagacherie, P. and Voltz, M., 2015. Managing ditches for agroecological engineering of landscape. A review. Agronomy for Sustainable Development, 35(3), pp.999-1020.

Dosskey, M.G., 2001. Toward quantifying water pollution abatement in response to installing buffers on crop land. Environmental Management, 28(5), pp.577-598.

Dosskey, M.G. and Qiu, Z., 2011. Comparison of Indexes for Prioritizing Placement of Water Quality Buffers in Agricultural Watersheds 1. JAWRA Journal of the American Water Resources Association, 47(4), pp.662-671.

Downing, J.A., 2010. Emerging global role of small lakes and ponds: little things mean a lot. Limnetica, 29(1), pp.0009-24.

Downing, J.A., Prairie, Y.T., Cole, J.J., Duarte, C.M., Tranvik, L.J., Striegl, R.G., McDowell, W.H., Kortelainen, P., Caraco, N.F., Melack, J.M. and Middelburg, J.J., 2006. The global abundance and size distribution of lakes, ponds, and impoundments. Limnology and Oceanography, 51(5), pp.2388-2397.

Estrada, V.E.E. and Hernandez, D.E.A., 2002. Treatment of piggery wastes in waste stabilization ponds. Water Science and Technology, 45(1), pp.55-60.

Ferreira, M. and Beja, P., 2013. Mediterranean amphibians and the loss of temporary ponds: Are there alternative breeding habitats?. Biological Conservation, 165, pp.179-186.

Frantzeskaki, N., 2019. Seven lessons for planning nature-based solutions in cities. Environmental science & policy, 93, pp.101-111.

Frédette, C., Grebenshchykova, Z., Comeau, Y. and Brisson, J., 2019. Evapotranspiration of a willow cultivar (Salix miyabeana SX67) grown in a full-scale treatment wetland. Ecological engineering, 127, pp.254-262.

Fiener, P., Auerswald, K. and Weigand, S., 2005. Managing erosion and water quality in agricultural watersheds by small detention ponds. Agriculture, Ecosystems & Environment, 110(3-4), pp.132-142.

García-Gutiérrez, C., Pachepsky, Y. and Martín, M.Á., 2018. Saturated hydraulic conductivity and textural heterogeneity of soils. Hydrology and Earth System Sciences, 22(7), pp.3923-3932.

Gallego, I., Pérez-Martínez, C., Sánchez-Castillo, P.M., Fuentes-Rodríguez, F., Juan, M. and Casas, J.J., 2015. Physical, chemical, and management-related drivers of submerged macrophyte occurrence in Mediterranean farm ponds. Hydrobiologia, 762(1), pp.209-222.

Gibbs, J.P., 2000. Wetland loss and biodiversity conservation. Conservation biology, 14(1), pp.314-317.

Gilbert, G., Tyler, G.A., Dunn, C.J. and Smith, K.W., 2005. Nesting habitat selection by bitterns Botaurus stellaris in Britain and the implications for wetland management. Biological conservation, 124(4), pp.547-553.

Gleason, R.A., Tangen, B.A., Laubhan, M.K., Kermes, K.E. and Euliss Jr, N.H., 2007. Estimating water storage capacity of existing and potentially restorable wetland depressions in a subbasin of the Red River of the North. USGS Northern Prairie Wildlife Research Center, p.89.

Gold, A.J., Groffman, P.M., Addy, K., Kellogg, D.Q., Stolt, M. and Rosenblatt, A.E., 2001. Landscape attributes as controls on groithd water nitrate removal capacity of riparian zones 1. JAWRA Journal of the American Water Resources Association, 37(6), pp.1457-1464.

Golden, H.E., Sander, H.A., Lane, C.R., Zhao, C., Price, K., D'amico, E. and Christensen, J.R., 2016. Relative effects of geographically isolated wetlands on streamflow: a watershed-scale analysis. Ecohydrology, 9(1), pp.21-38.

Grunewald, K., Richter, B., Meinel, G., Herold, H. and Syrbe, R.U., 2017. Proposal of indicators regarding the provision and accessibility of green spaces for assessing the ecosystem service "recreation in the city" in Germany. International Journal of Biodiversity Science, Ecosystem Services & Management, 13(2), pp.26-39.

Gumiero, B. and Boz, B., 2017. How to stop nitrogen leaking from a Cross compliant buffer strip?. Ecological Engineering, 103, pp.446-454.

Haase, D., Kabisch, S., Haase, A., Andersson, E., Banzhaf, E., Baró, F., Brenck, M., Fischer, L.K., Frantzeskaki, N., Kabisch, N. and Krellenberg, K., 2017. Greening cities–To be socially inclusive? About the alleged paradox of society and ecology in cities. Habitat International, 64, pp.41-48.

Hansen, A.T., Dolph, C.L. and Finlay, J.C., 2016. Do wetlands enhance downstream denitrification in agricultural landscapes?. Ecosphere, 7(10), p.e01516.

Herzon, I. and Helenius, J., 2008. Agricultural drainage ditches, their biological importance and functioning. Biological conservation, 141(5), pp.1171-1183.

Hickey, M.B.C. and Doran, B., 2004. A review of the efficiency of buffer strips for the maintenance and enhancement of riparian ecosystems. Water Quality Research Journal, 39(3), pp.311-317.

Hietala-Koivu, R., Lankoski, J. and Tarmi, S., 2004. Loss of biodiversity and its social cost in an agricultural landscape. Agriculture, ecosystems & environment, 103(1), pp.75-83.

Hill, A.R., 2018. Landscape hydrogeology and its influence on patterns of groundwater flux and nitrate removal efficiency in riparian buffers. JAWRA Journal of the American Water Resources Association, 54(1), pp.240-254.

Hill, A.R., 2019. Groundwater nitrate removal in riparian buffer zones: a review of research progress in the past 20 years. Biogeochemistry, 143(3), pp.347-369.

Hille, S., Andersen, D.K., Kronvang, B. and Baattrup-Pedersen, A., 2018. Structural and functional characteristics of buffer strip vegetation in an agricultural landscape–high potential for nutrient removal but low potential for plant biodiversity. Science of the Total Environment, 628, pp.805-814.

Hunt, P.G., Szögi, A.A., Humenik, F.J., Rice, J.M., Matheny, T.A. and Stone, K.C., 2002. Constructed wetlands for treatment of swine wastewater from an anaerobic lagoon. Transactions of the ASAE, 45(3), p.639.

Ibrahim, Y.A. and Amir-Faryar, B., 2018. Strategic Insights on the Role of Farm Ponds as Nonconventional Stormwater Management Facilities. Journal of Hydrologic Engineering, 23(6), p.04018023.

Ilyas, H., Masih, I. and van Hullebusch, E.D., 2020. Pharmaceuticals' removal by constructed wetlands: a critical evaluation and meta-analysis on performance, risk reduction, and role of physicochemical properties on removal mechanisms. Journal of Water and Health, 18(3), pp.253-291.

Jha, M.K., Chowdary, V.M., Kulkarni, Y. and Mal, B.C., 2014. Rainwater harvesting planning using geospatial techniques and multicriteria decision analysis. Resources, conservation and recycling, 83, pp.96-111.

Jlassi, W., Romero, M.E.N. and Ruiz, J.M.G., 2016. Modernization of new irrigated lands in a scenario of increasing water scarcity: from large reservoirs to small ponds. Cuadernos de investigación geográfica/Geographical Research Letters, (42), pp.233-259.

Jódar-Abellán, A., Albaladejo-García, J.A. and Prats, D., 2017. Artificial groundwater recharge. Review of the current knowledge of the technique.

Jordan, T.E., Whigham, D.F., Hofmockel, K.H. and Pittek, M.A., 2003. Nutrient and sediment removal by a restored wetland receiving agricultural runoff. Journal of environmental quality, 32(4), pp.1534-1547.

Kadam, A.K., Kale, S.S., Pande, N.N., Pawar, N.J. and Sankhua, R.N., 2012. Identifying potential rainwater harvesting sites of a semi-arid, basaltic region of Western India, using SCS-CN method. Water resources management, 26(9), pp.2537-2554.

Kadlec, R.H., 2012. Constructed marshes for nitrate removal. Critical Reviews in Environmental Science and Technology, 42(9), pp.934-1005.

Kayranli, B., Scholz, M., Mustafa, A. and Hedmark, Å., 2010. Carbon storage and fluxes within freshwater wetlands: a critical review. Wetlands, 30(1), pp.111-124.

King, S.E., Osmond, D.L., Smith, J., Burchell, M.R., Dukes, M., Evans, R.O., Knies, S. and Kunickis, S., 2016. Effects of Riparian Buffer Vegetation and Width: A 12-Year Longitudinal Study. Journal of environmental quality, 45(4), pp.1243-1251.

Knight, R.L., Payne Jr, V.W., Borer, R.E., Clarke Jr, R.A. and Pries, J.H., 2000. Constructed wetlands for livestock wastewater management. Ecological engineering, 15(1-2), pp.41-55.

Kröger, R., Dunne, E.J., Novak, J., King, K.W., McLellan, E., Smith, D.R., Strock, J., Boomer, K., Tomer, M. and Noe, G.B., 2013. Downstream approaches to phosphorus management in agricultural landscapes: regional applicability and use. Science of the Total Environment, 442, pp.263-274.

Kumar, T. and Jhariya, D.C., 2017. Identification of rainwater harvesting sites using SCS-CN methodology, remote sensing and Geographical Information System techniques. Geocarto International, 32(12), pp.1367-1388.

Kumwimba, M.N., Meng, F., Iseyemi, O., Moore, M.T., Zhu, B., Tao, W., Liang, T.J. and Ilunga, L., 2018. Removal of non-point source pollutants from domestic sewage and agricultural runoff by vegetated drainage ditches (VDDs): Design, mechanism, management strategies, and future directions. Science of the Total Environment, 639, pp.742-759.

Lajeunesse, M.J., 2016. Facilitating systematic reviews, data extraction and meta-analysis with the metagear package for R. Methods in Ecology and Evolution, 7(3), pp.323-330.

Lane, C.R. and D'Amico, E., 2010. Calculating the ecosystem service of water storage in isolated wetlands using LiDAR in North Central Florida, USA. Wetlands, 30(5), pp.967-977.

Lane, C.R., Leibowitz, S.G., Autrey, B.C., LeDuc, S.D. and Alexander, L.C., 2018. Hydrological, Physical, and Chemical Functions and Connectivity of Non-Floodplain Wetlands to Downstream Waters: A Review. JAWRA Journal of the American Water Resources Association, 54(2), pp.346-371.

Leon, A., Tang, Y., Chen, D., Yolcu, A., Glennie, C. and Pennings, S., 2018. Dynamic management of water storage for flood control in a wetland system: a case study in Texas. Water, 10(3), p.325.

Liebe, J., Van De Giesen, N. and Andreini, M., 2005. Estimation of small reservoir storage capacities in a semi-arid environment: A case study in the Upper East Region of Ghana. Physics and Chemistry of the Earth, Parts A/B/C, 30(6-7), pp.448-454.

Ma, M., 2008. Multi-scale responses of plant species diversity in semi-natural buffer strips to agricultural landscapes. Applied Vegetation Science, 11(2), pp.269-278.

Machiwal, D., Dayal, D. and Kumar, S., 2017. Estimating water balance of small reservoirs in arid regions: a case study from Kachchh, India. Agricultural Research, 6(1), pp.57-65.

Mahmoud, S.H. and Tang, X., 2015. Monitoring prospective sites for rainwater harvesting and stormwater management in the United Kingdom using a GIS-based decision support system. Environmental earth sciences, 73(12), pp.8621-8638.

Mander, Ü., Dotro, G., Ebie, Y., Towprayoon, S., Chiemchaisri, C., Nogueira, S.F., Jamsranjav, B., Kasak, K., Truu, J., Tournebize, J. and Mitsch, W.J., 2014. Greenhouse gas emission in constructed wetlands for wastewater treatment: a review. Ecological Engineering, 66, pp.19-35.

Maucieri, C., Barbera, A.C., Vymazal, J. and Borin, M., 2017. A review on the main affecting factors of greenhouse gases emission in constructed wetlands. Agricultural and forest meteorology, 236, pp.175-193.

McCracken, D.I., Cole, L.J., Harrison, W. and Robertson, D., 2012. Improving the farmland biodiversity value of riparian buffer strips: Conflicts and compromises. Journal of environmental quality, 41(2), pp.355-363.

Meers, E., Tack, F.M.G., Tolpe, I. and Michels, E., 2008. Application of a full-scale constructed wetland for tertiary treatment of piggery manure: monitoring results. Water, air, and soil pollution, 193(1-4), pp.15-24.

Mioduszewski, W., 2012. Small water reservoirs–their function and construction. Journal of Water and Land Development, 17(1), pp.45-52.

Mitsch, W.J., Bernal, B., Nahlik, A.M., Mander, Ü., Zhang, L., Anderson, C.J., Jørgensen, S.E. and Brix, H., 2013. Wetlands, carbon, and climate change. Landscape Ecology, 28(4), pp.583-597.

Moore, M.T., Bennett, E.R., Cooper, C.M., Smith Jr, S., Shields Jr, F.D., Milam, C.D. and Farris, J.L., 2001. Transport and fate of atrazine and lambda-cyhalothrin in an agricultural drainage ditch in the Mississippi Delta, USA. Agriculture, Ecosystems & Environment, 87(3), pp.309-314.

Morris, J., Bailey, A.P., Lawson, C.S., Leeds-Harrison, P.B., Alsop, D. and Vivash, R., 2008. The economic dimensions of integrating flood management and agri-environment through washland creation: a case from Somerset, England. Journal of Environmental Management, 88(2), pp.372-381.

Nagarajan, M., Seshadri, S., Vamshi, D.Y. and Prasad, N.M., 2015. Runoff Estimation and Identification of Water Harvesting Structures for Groundwater Recharge Using Geo-Spatial Techniques. Jordan Journal of Civil Engineering, 9(4).

Napoli, M., Cecchi, S., Orlandini, S. and Zanchi, C.A., 2014. Determining potential rainwater harvesting sites using a continuous runoff potential accounting procedure and GIS techniques in central Italy. Agricultural Water Management, 141, pp.55-65.

Needelman, B.A., Kleinman, P.J., Strock, J.S. and Allen, A.L., 2007. Drainage ditches improved management of agricultural drainage ditches for water quality protection: an overview. Journal of Soil and Water Conservation, 62(4), pp.171-178.

Nivala, J., Kahl, S., Boog, J., van Afferden, M., Reemtsma, T. and Müller, R.A., 2019. Dynamics of emerging organic contaminant removal in conventional and intensified subsurface flow treatment wetlands. Science of The Total Environment, 649, pp.1144-1156.

O'Geen, A.T., Budd, R., Gan, J., Maynard, J.J., Parikh, S.J. and Dahlgren, R.A., 2010. Mitigating nonpoint source pollution in agriculture with constructed and restored wetlands. In Advances in Agronomy (Vol. 108, pp. 1-76). Academic Press.

Ogilvie, A., Belaud, G., Massuel, S., Mulligan, M., Le Goulven, P. and Calvez, R., 2016. Assessing floods and droughts in ungauged small reservoirs with long-term Landsat imagery. Geosciences, 6(4), p.42.

Ouyang, Y., Paz, J.O., Feng, G., Read, J.J., Adeli, A. and Jenkins, J.N., 2017. A model to estimate hydrological processes and water budget in an irrigation farm pond. Water Resources Management, 31(7), pp.2225-2241.

Papaevangelou, V.A., Gikas, G.D. and Tsihrintzis, V.A., 2012. Evaluation of evapotranspiration in small on-site HSF constructed wetlands. Journal of Environmental Science and Health, Part A, 47(5), pp.766-785.

Qiu, J., Shen, Z., Chen, L., Xie, H., Sun, C. and Huang, Q., 2014. The stakeholder preference for best management practices in the three gorges reservoir region. Environmental management, 54(5), pp.1163-1174.

Ramakrishnan, D., Bandyopadhyay, A. and Kusuma, K.N., 2009. SCS-CN and GIS-based approach for identifying potential water harvesting sites in the Kali Watershed, Mahi River Basin, India. Journal of earth system science, 118(4), pp.355-368.

Raicy, M.C. and Elango, L., 2020. Percolation pond with recharge shaft as a method of managed aquifer recharge for improving the groundwater quality in the saline coastal aquifer. Journal of Earth System Science, 129(1), pp.1-12.

Raymond, C.M., Frantzeskaki, N., Kabisch, N., Berry, P., Breil, M., Nita, M.R., Geneletti, D. and Calfapietra, C., 2017. A framework for assessing and implementing the co-benefits of nature-based solutions in urban areas. Environmental Science & Policy, 77, pp.15-24.

Recchia, L., Cini, E. and Corsi, S., 2010. Multicriteria analysis to evaluate the energetic reuse of riparian vegetation. Applied Energy, 87(1), pp.310-319.

Rejani, R., Rao, K.V., Srinivasa Rao, C.H., Osman, M., Sammi Reddy, K., George, B., Pratyusha Kranthi, G.S., Chary, G.R., Swamy, M.V. and Rao, P.J., 2017. Identification of potential rainwater-harvesting sites for the sustainable management of a semi-arid watershed. Irrigation and drainage, 66(2), pp.227-237.

Robertson, W.D. and Merkley, L.C., 2009. In-stream bioreactor for agricultural nitrate treatment. Journal of Environmental Quality, 38(1), pp.230-237.

Rodrigues, L.N., Sano, E.E., Steenhuis, T.S. and Passo, D.P., 2012. Estimation of small reservoir storage capacities with remote sensing in the Brazilian Savannah Region. Water resources management, 26(4), pp.873-882.

Rolke, D., Jaenicke, B., Pfaender, J. and Rothe, U., 2018. Drainage ditches as important habitat for species diversity and rare species of aquatic beetles in agricultural landscapes (Insecta: Coleoptera). Journal of Limnology, 77(3).

Roost, N., Cai, X.L., Molden, D. and Cui, Y.L., 2008. Adapting to intersectoral transfers in the Zhanghe Irrigation System, China: Part I. In-system storage characteristics. Agricultural water management, 95(6), pp.698-706.

Russi, D., ten Brink, P., Farmer, A., Badura, T., Coates, D., Förster, J., Kumar, R. and Davidson, N., 2013. The economics of ecosystems and biodiversity for water and wetlands. IEEP, London and Brussels, 78.

Sabater, S., Butturini, A., Clement, J.C., Burt, T., Dowrick, D., Hefting, M., Matre, V., Pinay, G., Postolache, C., Rzepecki, M. and Sabater, F., 2003. Nitrogen removal by riparian buffers along a European climatic gradient: patterns and factors of variation. Ecosystems, 6(1), pp.0020-0030.

Salazar, S., Francés, F., Komma, J., Blume, T., Francke, T., Bronstert, A. and Bloschl, G., 2012. A comparative analysis of the effectiveness of flood management measures based on the concept of'retaining water in the landscape'in different European hydro-climatic regions. Natural Hazards and Earth System Sciences (NHESS), 12(11), pp.3287-3306.

Sallwey, J., Bonilla Valverde, J.P., Vásquez López, F., Junghanns, R. and Stefan, C., 2019. Suitability maps for managed aquifer recharge: a review of multi-criteria decision analysis studies. Environmental Reviews, 27(2), pp.138-150.

Sawunyama, T.E.N.D.A.I., Senzanje, A. and Mhizha, A., 2006. Estimation of small reservoir storage capacities in Limpopo River Basin using geographical information systems (GIS) and remotely sensed surface areas: Case of Mzingwane catchment. Physics and Chemistry of the Earth, Parts A/B/C, 31(15-16), pp.935-943.

Schmidt, S., Manceur, A. M., & Seppelt, R. (2016). Uncertainty of monetary valued ecosystem services–value transfer functions for global mapping. PloS one, 11(3)

Singh, L.K., Jha, M.K. and Chowdary, V.M., 2017. Multi-criteria analysis and GIS modeling for identifying prospective water harvesting and artificial recharge sites for sustainable water supply. Journal of Cleaner Production, 142, pp.1436-1456.

Singhai, A., Das, S., Kadam, A.K., Shukla, J.P., Bundela, D.S. and Kalashetty, M., 2019. GIS-based multi-criteria approach for identification of rainwater harvesting zones in upper Betwa sub-basin of Madhya Pradesh, India. Environment, Development and Sustainability, 21(2), pp.777-797.

Stehle, S., Elsaesser, D., Gregoire, C., Imfeld, G., Niehaus, E., & Passeport, E. et al., 2011. Pesticide Risk Mitigation by Vegetated Treatment Systems: A Meta-Analysis. Journal Of Environmental Quality, 40(4), pp.1068-1080.

Strand, J.A. and Weisner, S.E., 2013. Effects of wetland construction on nitrogen transport and species richness in the agricultural landscape—Experiences from Sweden. Ecological Engineering, 56, pp.14-25.

Stutter, M.I., Chardon, W.J. and Kronvang, B., 2012. Riparian buffer strips as a multifunctional management tool in agricultural landscapes: introduction. Journal of environmental quality, 41(2), pp.297-303.

Stutter, M., Kronvang, B., Ó hUallacháin, D. and Rozemeijer, J., 2019. Current insights into the effectiveness of riparian management, attainment of multiple benefits, and potential technical enhancements. Journal of environmental quality, 48(2), pp.236-247.

Teatini, P., Comerlati, A., Carvalho, T., Gütz, A.Z., Affatato, A., Baradello, L., Accaino, F., Nieto, D., Martelli, G., Granati, G. and Paiero, G., 2015. Artificial recharge of the phreatic aquifer in the upper Friuli plain, Italy, by a large infiltration basin. Environmental earth sciences, 73(6), pp.2579-2593.

Teurlincx, S., Verhofstad, M.J., Bakker, E.S. and Declerck, S.A., 2018. Managing successional stage heterogeneity to maximize landscape-wide biodiversity of aquatic vegetation in ditch networks. Frontiers in plant science, 9, p.1013.

Thorslund, J., Jarsjo, J., Jaramillo, F., Jawitz, J.W., Manzoni, S., Basu, N.B., Chalov, S.R., Cohen, M.J., Creed, I.F., Goldenberg, R. and Hylin, A., 2017. Wetlands as large-scale nature-based solutions: Status and challenges for research, engineering and management. Ecological engineering, 108, pp.489-497.

Tiner, R.W., 2003. Geographically isolated wetlands of the United States. Wetlands, 23(3), pp.494-516.

Ueno, K., Natsuka, I., Sato, S., Onjo, N., Karma, T. and Tenzin, K., 2019. CONSTRUCTION OF EARTH FILL STRUCTURE FOR SMALL FARM POND BY USING BHUTANESE TRADITIONAL WALL MAKING METHOD. International Journal, 17(59), pp.127-132.

Verstraeten, G. and Poesen, J., 2002. Using sediment deposits in small ponds to quantify sediment yield from small catchments: possibilities and limitations. Earth Surface

Processes and Landforms: The Journal of the British Geomorphological Research Group, 27(13), pp.1425-1439.

Vidal, G., de Los Reyes, C.P. and Sáez, O., 2018. The Performance of Constructed Wetlands for Treating Swine Wastewater under Different Operating Conditions. Constructed Wetlands for Industrial Wastewater Treatment, pp.203-221.

Vidon, P.G., Welsh, M.K. and Hassanzadeh, Y.T., 2019. Twenty years of riparian zone research (1997–2017): Where to next?. Journal of Environmental Quality, 48(2), pp.248-260.

Vymazal, J., 2007. Removal of nutrients in various types of constructed wetlands. Science of the total environment, 380(1-3), pp.48-65.

Vymazal, J. and Březinová, T., 2015. The use of constructed wetlands for removal of pesticides from agricultural runoff and drainage: a review. Environment international, 75, pp.11-20.

Vymazal, J. and Březinová, T.D., 2018. Removal of nutrients, organics and suspended solids in vegetated agricultural drainage ditch. Ecological Engineering, 118, pp.97-103.

Wagner, M.M., 2008. Acceptance by knowing? The social context of urban riparian buffers as a stormwater best management practice. Society and Natural Resources, 21(10), pp.908-920.

Wisser, D., Frolking, S., Douglas, E.M., Fekete, B.M., Schumann, A.H. and Vörösmarty, C.J., 2010. The significance of local water resources captured in small reservoirs for crop production–A global-scale analysis. Journal of Hydrology, 384(3-4), pp.264-275.

Zak, D., Stutter, M., Jensen, H.S., Egemose, S., Carstensen, M.V., Audet, J., Strand, J.A., Feuerbach, P., Hoffmann, C.C., Christen, B. and Hille, S., 2019. An assessment of the multifunctionality of integrated buffer zones in northwestern Europe. Journal of environmental quality, 48(2), pp.362-375.

Zhang, X., Liu, X., Zhang, M., Dahlgren, R.A. and Eitzel, M., 2010. A review of vegetated buffers and a meta-analysis of their mitigation efficacy in reducing nonpoint source pollution. Journal of environmental quality, 39(1), pp.76-84.

Books

Abdi H. and L.J. Williams (2010). Multiple Correspondence Analysis. In Neil Salkind (Ed.), Encyclopedia of Research Design. Thousand Oaks, CA: Sage. 2010.

Bettes, R., 1996. Infiltration drainage – manual of good practice, R156, CIRIA, London, UK (ISBN: 978-0-86017-457-8)

Ioannidou, V. and Stefanakis, A.I., 2020. The Use of Constructed Wetlands to Mitigate Pollution from Agricultural Runoff. In Contaminants in Agriculture (pp. 233-246). Springer, Cham.

Kadlec, R.H. and Wallace, S., 2009. Treatment wetlands. CRC press.

Maliva, R.G., 2019. Anthropogenic Aquifer Recharge. Springer, Cham (Switzerland).

Reed S.C., Crites R.W., Mittlebrooks E.J. (1995). Natural systems for waste management and treatment, 2nd Ed. Mc Graw Hill inc., N.Y.

Rolfe, J., Johnston, R. J., Rosenberger, R. S., & Brouwer, R. (2015). Introduction: Benefit Transfer of Environmental and Resource Values. In Benefit Transfer of Environmental and Resource Values (pp. 3-17). Springer, Dordrecht.

Proceeding

Nardini A., R. Soncini-Sessa e J. Zuleta (1988). "Effects of Reclamation Plans on Water Shortages and Flood Protection". Atti del IV Symposium on System Analysis Applied to Management of Water Resources, pag. 263-268, (11-13 Ottobre 1988), Rabat, Marocco.

Reports

Church, A., Fish, R., Haines-Young, R., Mourato, S., Tratalos, J.A., Stapleton, L., Willis, C., Coates, P., Gibbons, S., Leyshon, C. and Potschin, M., 2014. UK NEAFO Work Package 5: Cultural Ecosystem Services and Indicators.

European Commission (2020a) Biodiversity and Nature-based Solutions: analysis of EU-funded projects. Luxembourg: Publications Office of the European Union

European Commission (2020b) Nature-based Solutions for Climate Mitigation. Analysis of EU-funded projects. Luxembourg: Publications Office of the European Union

Gao, S., 2010. The amenity value of wetlands (Doctoral dissertation).

Food and Agriculture Organization of the United Nations (FAO) 2014. Compendium on Rainwater Harvesting for Agriculture in the Caribbean Sub region. Concepts, calculations and definitions for small, rain-fed farm systems.

Final report of the project "Riduzione del carico inquinante generato dai reflui zootecnici nell'area del bacino scolante della laguna veneta – RiduCaReflui" finanziato dalla Regione Veneto con D.G.R. 4031 del 30/12/2008" http://riducareflui.venetoagricoltura.org/index.php/59-progetti-in-home/riducareflui/126-pubblicazioni-riducareflui (In Italian, access April 2020)

Williams, L., Harrison, S. and O'Hagan A M. (2012) The use of wetlands for flood attenuation. Report for An Taisce by Aquatic Services Unit, University College Cork.

UN-Water. 2018. The United Nations World Water Development Report 2018: Nature-Based Solutions for Water. Paris, UNESCO.

Guidelines

Websites

Natural Water Retention Measures (NWRM) website (nwrm.eu)

OECD (2020), Inflation (CPI) (indicator). doi: 10.1787/eee82e6e-en (Accessed on 16 March 2020)

OECD (2020), Exchange rates (indicator). doi: 10.1787/037ed317-en (Accessed on 16 March 2020)

WB (2020). World Development Indicators, GDP per capita, PPP (current international $). (Accessed on 16 March 2020)

Database

Trabucco, A., and Zomer, R.J. 2018. Global Aridity Index and Potential Evapo-Transpiration (ET0) Climate Database v2. CGIAR Consortium for Spatial Information (CGIAR-CSI). Published online, available from the CGIAR-CSI GeoPortal at https://cgiarcsi.community

LWDB – Constructed wetland for livestock wastewater management 1997. CH2MHILL